ARTIFICIAL INTELLIGENCE (AI) IN RADIOLOGY PRACTICES: THE QUANTITATIVE ANALYSIS OF THE RADIOLOGY PROFESSIONALS' PERCEPTIONS OF AI USEFULNESS

by

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Author's Declaration

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Abstract

Artificial Intelligence (AI) in Radiology Practices: The Quantitative Analysis of the Radiology Professionals' Perceptions of AI Usefulness

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Despite the many advantages AI provides to the healthcare sector, AI use in medical imaging is in its infancy. Given the importance of radiology professionals' role, successful AI integration in radiology necessitate their acceptance. The purpose of this thesis is to explore radiology professionals' perception of AI usefulness in improving healthcare quality. A major part of this thesis is dedicated to the quantitative analysis of the secondary dataset collected through an online survey administered among radiology professionals in the UAE. Besides understanding how radiology professionals perceive AI utilization, this study intended to develop a framework reflecting this perception via evaluating the existing theories. The study finding showed that factors such as AI functionality; AI experience; feeling toward AI; and AI clinical characteristics have the most significant contribution to explaining how radiology professionals perceive AI. The study findings can help in successful AI implementation toward improving the patient's quality of care.

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1. Introduction

Artificial intelligence (AI) is a branch of computer science with origins in the 1940s (Turing, 1950) which aims to create computational systems with enhanced analytical and predictive abilities. Typically, such systems are built to address complicated data-intensive issues that demand the prediction or reasoning about their underlying phenomena (Azuaje, 2019). In fact, AI refers to the theory and creation of computer systems that can accomplish activities that would otherwise need human intelligence (Georgevici & Terblanche, 2019). It is important to note that, AI research focused on knowledge-based techniques rather than empirically derived algorithms (Edwards et al., 2020). The most successful branch of AI is Machine Learning (ML), which is concerned with creating programs that can learn from data (Jordan & Mitchell, 2015). In ML, mathematical and statistical methods are used to learn from large datasets (Shimizu & Nakayama, 2020). Generally, ML systems do not rely solely on human knowledge, instead, it employs algorithms to recognize data patterns in a large number of example cases and match new events to the previously found patterns (Harrison et al., 2021). ML also includes Deep Neural Networks (DNN), that is characterized by the use of multilayered artificial neural networks (Shimizu & Nakayama, 2020). DNN represents a set of innovative approaches that, when combined, have shown significant gains in performance over existing best-in-class ML algorithms. For example, these approaches have revolutionized image classifications and speech recognition due to their excellent accuracy (LeCun et al., 2015, as cited in Shimizu & Nakayama, 2020). DNNs that have been trained on millions of non-medical images are subsequently repurposed for medical applications through fine-tuned training using thousands of biomedical images (Yu et al., 2018).

AI has been shown to accurately diagnose a range of medical conditions. In a multihospital clinical study, researchers demonstrated that an AI agent successfully offered treatment recommendations for congenital cataracts that are as effective as those made by ophthalmologists (Long et al., 2017). Another study, based on regular clinical data from over 350,000 patients, found that ML achieved a dramatically high prediction accuracy of cardiovascular risk by accurately identifying 355 more patients who developed cardiovascular disease than the established approach (Weng et al, 2017). Additionally, as argued by Yu et al., (2018), many studies indicated that AI systems may improve clinical decision-making; illness diagnosis; the identification of previously undiscovered imaging or genetic patterns linked to patient characteristics; and surgical therapies for a variety of human diseases. Moreover, AI applications can assist in addressing healthcare needs in areas where specialists are unavailable (Yu et al., 2018). According to Luchini et al. (2021), research has shown that cancer radiology is the oncology-related discipline with the most AI-based devices, accounting for the bulk of approved devices. This is followed by Pathology, radiation oncology, gastroenterology, clinical oncology, and gynecology. Overall, the field of cancer diagnostics accounts for more than 80% of all approved AI-associated algorithms.

As suggested by pattern recognition and machine learning capabilities of AI technology, one of the most promising fields for the use of AI in medicine is radiology (Joshi & Morley, 2019). In fact, Medical Image (MI)-based diagnosis is considered to be one of the most successful applications of AI in healthcare using DNN (Yu et al., 2018). When complicated patterns in imaging data are automatically recognized by AI, "quantitative, rather than qualitative, judgements of radiographic characteristics" are provided (Hosny et al., 2018).

Studies claimed that the AI algorithms used for the diagnosis of thoracic cancer have been shown to be equal to or even surpass radiologists' performance for single anomalies on chest X-rays (Chassagnon et al., 2020; Car et al., 2019). With the support of contemporary ML methods, Many AI-based radiology applications, such as the detection of lung nodules using CT images (Van Ginneken et al., 2015), diagnosis of pulmonary tuberculosis (Lakhani & Sundaram, 2017), and breast-mass detection utilizing mammography images (Samala et al., 2016) have attained professional-level diagnostic accuracy (Yu et al., 2018). For instance, in breast cancer, the diagnosis AI algorithm in mammography has been used effectively in recognizing imaging abnormalities in a timely and accurate manner (Kim et al., 2020).

As argued by Basilio et al., (2022), many research investigations have found that the adoption of Digital Radiology (DR) has resulted in significant advances in the field of organ and functional diagnosis. Today, DR encompasses a broad range of diagnostic modalities, including fields such as Magnetic Resonance Imaging (MRI) and Echography that are not directly connected to ionizing radiation (Basilio et al., 2022). AI may be beneficial in the field of DR, both in terms of clinical diagnosis (by assisting categorization efforts with image improvement, feature evaluation, and recognition) and patient management (Giansanti & Di Basilio, 2022). Given that the timeline is very critical in the diagnostic procedure particularly when there are urgent or life-threatening disorders present (Thrall et al., 2018), in addition to enhancing diagnosis accuracy (Fryback & Thornbury, 1991), a range of significant practical issues in radiology practices may be addressed using AI applications. This includes pre-analyzing cases (where observer fatigue may be critical), prioritizing cases, enhancing the quality of

reconstructed images, and extracting important data from images that are not visible to the human eye (Thrall et al., 2018).

The rising demands on radiology departments along with the fast-evolving technologies providing enormous and complex datasets have prioritized the use of AI-based developments in the field of radiology (Joshi & Morley, 2019). According to the NHS (2020), 44.9 million imaging tests were carried out in NHS England alone in 2019. Due to the acute shortage that the UK and many other countries are currently experiencing, the radiology departments are under increasing pressure to perform quick, high-throughput evaluations of medical images (New Reports Put UK Radiologist Shortages into Focus (the Royal College of Radiologists, 2020).

In the clinical setting, although ML may be better than existing approaches at identifying and predicting subgroups with a better or poorer response to clinical therapies, in the absence of large samples, good quality data, and contextual knowledge, false positive and false negative outcomes might also arise (Zhang, 2019, as cited in Scott, 2021). Since ML-based approaches rely largely on huge volumes of high-quality training data, it is critical to acquire data that accurately represent the target patient population (Yu et al., 2018). However, there are intrinsic challenges to the collection and curation of clinical data due to privacy concerns (Rieke et al,2020). Even though FDA plays a significant role in authorizing AI applications for clinical use, it is still not clear how AI programs will be validated and how AI applications' liability will be impacted by the "black box" nature of AI algorithms (Thrall et al., 2018).

Given that radiology is at the forefront of AI integration advancements in healthcare, radiology professionals have a significant role in AI adoption in healthcare in general. Unfortunately, available literature reviewed little about how radiology professionals react to this

novel technology or its implications for its future potential usage (Chen et al., 2021). Therefore, the aim of the current study is to explore the perception radiology professionals may have on the use of AI in radiology practices to improve healthcare quality and patient outcomes. Radiology professionals (radiologists and radiographers) who are willing to devote additional time to AI in their already busy clinical schedules are often considered early adopters. For the early majority to start using AI tools and for a tipping point to be reached, the next phase will be driven by these proactive medical professionals (E. Rogers, 1962). This is essential because it will allow for extensive validation of AI technologies in clinical settings while end-user feedback is being generated. AI adoption by radiology professionals may also avoid the common scenario of data being utilized for profit instead of enhancing patient care (Geis et al., 2019). Therefore, in this research study rather than considering any other healthcare professionals working in any department than medical imaging, the study's primary focus is on the radiology professionals only and their perception of AI usefulness.

While studies on the utilization of AI applications are common in the Management Information Systems literature, the earlier studies often did not consider a well-established theoretical framework. Through conducting the quantitative analysis of the survey results, the major contribution of this thesis is to evaluate the existing theories of technology perceptions in order to contribute to developing the best theory that reflects how AI is perceived by radiology professionals. Therefore, the current study intended to partially adopt the integrated model of the Technology Acceptance Model (TAM) and Task Technology Fit (TTF) proposed by Dishaw and Strong (1999). The study intended to contribute to the existing literature on healthcare technology perception by evaluating the relationship between TTF, TAM, and radiology

professionals' AI perceptions.

Through conducting a quantitative analysis of the secondary data, this study aims to answer, two main research questions: 1) How do radiology professionals perceive the usefulness of AI applications in radiology settings? 2) what are the main predictors of radiology professionals' perception of AI usefulness? In parallel to answering the thesis's research questions, the researcher intended also to propose the best theoretical model that represents the perception radiology professionals may have toward AI usefulness in radiology practices. The study's findings will provide further information on the factors that impact the application of AI in radiology practices and will assist healthcare policymakers and administrators in successfully planning and integrating AI in Medical Imaging practices in order to achieve a more effective disease diagnosis and improved patient outcomes.

This thesis consists of three main sections. First, it explains different research literature in the field of AI perception in radiology and describes a gap in the available literature. Second, it explains the method adopted by the researchers of this study. Third, it offers suggestions for future research and provides recommendations for technology developers and designers.

2. Literature Review

2.1. AI Applications in Radiology

During the last decade, the number of articles about AI in radiology has grown exponentially over the last few years going from 100–150 to 700–800 scholarly publications annually (Pesapane et al., 2018). The available literature shows that machine learning-based algorithms can potentially enhance a number of radiology workflow steps, including patient

triage and scheduling (van Ginneken, 2019); support in clinical decisions (Bal et al., 2014; Bennett & Hauser, 2013); pathological finding detection and interpretation (Ciompi et al., 2017; Herweh et al., 2016); post-processing (Pedoia et al., 2016; Xiong et al., 2019); radiation dose estimation (Wu et al., 2017); radiation dose control (Bray (Buurman et al., 2015).

According to Van Leeuwen et al. (2021), the ultimate aim of AI applications in radiology practices can be summarized as (1) increasing workflow efficiency, (2) reducing reading time, (3) decreasing dose and contrast agents, (4) earlier disease detection, (5) enhanced diagnostic accuracy, and (6) more personalized diagnostics. According to Willemink and Nol (2018), image reconstruction and post-processing are being advanced using AI algorithms. This allows for high image quality at a low radiation dose (Van Leeuwen et al., 2021).

Considering the increasing expenses of healthcare globally, making efficient use of limited resources is an important task. AI may help with this in both clinical and non-clinical ways. For instance, AI software may contribute to the scheduling of medical imaging appointments and forecast no-shows even before a patient visits the radiology department. This may result in more efficient scheduling (Chong et al., 2020). Also, as argued by Van Leeuwen et al. (2021), AI algorithms can help in forecasting clinical risks and outcomes based on individual characteristics. This may lead to better health outcomes and facilitate resource allocation which ultimately may result in a more effective clinical workflow. For instance, in the field of neurology, the brain volume measurements generated using AI algorithms were used to forecast the need for additional invasive testing to identify Alzheimer's disease, while additional biomarker testing was only being performed on populations who really needed it (Rhodius-Meester et al., 2020). To ensure that AI applications can provide the value required by medical

professionals and patients, they should be integrated into the clinical workflow, including administrative operations, clinical duties, and patient education (Reddy et al.,2019).

The adoption of AI applications has the potential of lowering physicians' workloads and enhancing the quality of patient care (Aung et al., 2021). AI could help mine large amounts of healthcare data, synthesize patient records, summarize and highlight essential health concerns for practitioners (Dilsizian & Siegel, 2013). AI might also be used as a preliminary screening tool in medical imaging interpretation, highlighting those of concern so that the physician's attention can be drawn to serious situations faster. This may reduce physicians' workload and eliminates the need for additional investigation (Aung et al., 2021). Additionally, studies revealed that AI outperforms humans with respect to accuracy metrics (Jones et al., 2018). A good example is a deep learning-based computer-aided diagnosis (CAD) system, used to classify breast tumours as benign or malignant and has greater diagnostic sensitivity and reliability than humans (Cheng et al., 2016). Aside from compensating for human mistakes, AI may also help clinicians make better clinical decisions by offering up-to-date information on clinical guidelines and advances (Aung et al., 2021). In medical imaging, apart from engineering aspects, the adoption of AI will necessitate proper knowledge dissemination to radiologists, other healthcare professionals, and patients. All these parties need to be informed about the advantages and potential drawbacks of AI technologies and how they will influence clinical practices (Wiggins et al., 2021). To have a successful AI implementation and to achieve more efficient AI utilization in medical imaging settings, it is essential to learn about how radiology professionals perceive using AI applications and whether they perceive AI to be a valuable tool for accomplishing their tasks or not. This is important since the perceived usefulness of technology can influence its actual use (Dishaw &

Strong, 1999). The systematic review conducted by Santomartino and Yi (2022) shows that the majority of radiology professionals and medical student participants in the study perceive AI's usefulness for radiology and are generally optimistic about AI application. However, most of them claimed a lack of formal education or training in AI applications. The survey conducted by Jungmann et al. (2020) found that only a small percentage of radiology professionals are confident in the outcomes of AI applications. The same study showed that over 90% of participants thought using AI in medicine will increase its effectiveness. This is similar to the result of Gong et al. (2019) study, where more than 90% of Canadian medical students thought that AI will improve radiology professionals' capabilities and increase their productivity. The following section is dedicated to outlining the concerns associated with the implementation of AI in medical imaging settings.

2.2. AI Challenges in Radiology Practices

Despite the numerous advantages of AI applications, there are significant challenges facing the process of implementing AI into radiology practices at every level of the AI adoption process, including, data collection, technological development, clinical implementation, ethical assessment, and patient acceptance (Aung et al., 2021). First, for their training, AI models require large, annotated patient datasets (Johnson, et al.,2018). This constitutes a major challenge to AI implementation as it is intimately tied to the concerns about data privacy and security, patient consent, and data collection standards and regulations. However, research showed that this problem could be mitigated to some extent by strengthening personal data restrictions and legislation, such as the General Data Protection Regulation (GDPR) (The European Commission,

2018) and Health Research Regulations (Data Protection Act, 2018), which were imposed across Europe in 2018. The development of AI technology is the next challenge. Research revealed that overfitting may exist when the system learns non-relevant correlations between patient variables and outcomes. This may result in algorithm prediction using incorrect features due to having too many variables relative to outcomes. The 'black-box' problem is another common critique of AI technologies which refers to the fact that AI predictions are not explainable. Legally, this might raise a problem if the recommendations of AI applications are incorrect. When it comes to AI applications, the issue of accountability is very critical too (Aung et al., 2021).

To gain a deeper knowledge of the factors influencing the implementation of AI applications into radiology, the next section will focus on the most frequently discussed topics within the literature including AI ethical concerns; Trust in AI applications; AI governance; AI infrastructure and data privacy.

2.2.1. AI Ethical Concern

Despite the benefits of AI applications in radiology practices, some radiologists may be hesitant to use AI-based tools due to factors such as financial issues, lack of regulations, lack of knowledge, a fear of making mistakes, or the possibility of losing their employment or authority (Alsharif et al.,2022). The ethical considerations of AI adoption by radiologists are one of the key issues. Generally, ethical concerns about AI range from discrimination, job loss, and inequality to security and safety (Hagendorff, 2019, as cited in Baird & Schuller,2020).

Regardless of the claim that some radiology specialties may be replaced by AI in the future (Hoek et al., 2019), experts agree that the complicated job of radiologists cannot be

managed by AI applications alone (Choy et al., 2018; Tang et al.,2018). According to Langlotz (2019), there are a number of factors, including the "long tail" of disease distribution, which accounts for uncommon diseases, making it unlikely that radiologists would quickly disappear from healthcare systems. Using the example of autopilot for human pilots, Langlotz (2019) emphasized the straightforward factual affirmation: Radiologists who don't use AI will be replaced by radiologists who do. With reference to one of the largest surveys to date, the research conducted by Huisman et al. (2021) investigating the knowledge and attitude of 1,041 radiologists and residents in Europe and beyond, although the fear of being replaced by AI still occurs in the radiology society according to 39% of respondents (n = 401), an open and proactive attitude towards AI was also noted in nearly half of the respondents (48%, n = 501). According to the findings of the same survey, there is evidence of a substantial independent association between an open and proactive attitude toward AI and gender (male); age (younger); education; use of social media, and informatics/statistics knowledge and familiarity. This suggests that radiology professionals particularly those who still have most of their careers ahead of them and who are innately more motivated in science and/or technology have a positive attitude toward AI's recent technological development (Huisman et al., 2021). According to the same study, many studies have revealed that having a basic understanding of AI is independently correlated with both, fear of replacement and a lower likelihood of having an open and proactive attitude toward AI. This might be explained by the fact that radiology professionals who have only had a limited amount of exposure to AI may not be fully aware of its limitations and thus worry about losing their jobs. It is possible that this group is unaware that radiology professionals can be key players in the AI development, validation, and implementation into clinical practices because

they have less reference about AI and may believe the technology is more advanced than their own skills and experience (Huisman et al., 2021).

Besides lack of knowledge and fear of replacement, radiology professionals' accountability would constitute a serious challenge in AI adoption and might require regulation. (Pesapane et al., 2018). In fact, the primary ethical concern, aside from data privacy and safety, is accountability. Specifically, in the healthcare industry where poor judgments have serious repercussions, and the prevailing paradigm is that someone must be held accountable (Aung et al.,2021). The debate about Who will be accountable for the outcomes of AI is a heavily contested topic (Pesapane et al., 2018). It should be noted that this is a significant concern because it could fundamentally influence the role of radiology professionals within the healthcare systems (ESR, 2019). The results of the EuroAIM survey conducted in 2019 among members of European Society of Radiology (ESR), revealed that the majority of 675 ESR member participants showed a favourable attitude toward AI in general. Among all, 41% of the respondents believed that radiologists should be accountable for any medical mistakes, 41% proposed shared responsibility with other specialists, and 10.2% and 3.6% of responders proposed AI developers and insurance companies respectively. However, all respondents agreed that radiologists should be engaged in the creation and evaluation of AI systems (ESR, 2019). The study by Alsharif et al. (2022) revealed similar results, with the exception of radiologists' willingness to participate in the development of AI applications. The findings of the EuroAIM survey, along with other similar studies, show that accountability of results generated by AI still counts for an open challenge which requires legislation across Europe and other countries (ESR, 2019). According to the systematic review conducted by Santomartino and Yi (2022), it is not

entirely clear to what extent radiologists are willing to take legal or ethical responsibility, in fact in different studies, different types of respondents (e.g. Medical students or radiology attendings) showed a split of perceptions about who should be held accountable for such medical errors resulting from the use of AI: hospitals, the AI company or the radiology professionals. Unfortunately, it is still unclear who should be held accountable when things go wrong. Holding the physician responsible may seem unreasonable because they did not build or control the algorithm in any way, whereas holding the developer responsible seems too far away from the clinical context. Furthermore, the lack of industry regulations on the ethical application of AI in healthcare exacerbates the situation (Aung et al., 2021). Experts predict that AI-based technologies will also have an impact on radiology's ethical future in addition to its economic, scientific, and clinical futures (Jungmann et al., 2020).

Ethical concerns with AI systems would present a complicated issue that would necessitate EU and worldwide legislation (ESR, 2019). However, AI's implementation guidelines in healthcare are still being developed (Rock Health, 2021 as cited in Khafaji et al., 2022). This is a very important concern that generates interesting ethical and legal debates. As an example of how to preserve the privacy of patients, institutions should ensure that their big datasets are used appropriately (Tang et al., 2018). In this respect, the US Food and Drug Administration (FDA) has begun developing recommendations on how to evaluate the efficacy and safety of AI systems in order to better understand the extent to which AI may be ethically implemented in hospitals (Jiang et al., 2017). Therefore, it is crucial to provide a suitable training program to ensure that healthcare professionals are aware of their ethical and legal obligations with regard to data management (Loh, 2018). In many of the available studies, ethical and legal

concerns were identified as a barrier to the implementation of AI; nevertheless, many of the participants in the studies did not even identify these concerns as a problem. For instance, the findings of the study by Huisman et al. (2021b) reveal that only 62% (n = 630/1024) of respondents cited ethical and legal concerns as a barrier to AI adoption. It is therefore possible that a considerable proportion of respondents may not see privacy concerns and inadvertent harm caused by algorithms employed in medical devices as a problem. This shows that regulatory concerns, as well as the numerous biases and potential drawbacks brought on by using algorithms for diagnostic decision-making, are subjects that need to be further researched (Geis et al., 2019) and integrated into education (Huisman et al., 2021b).

To address these ethical challenges, industry-based research groups considered four major ethical considerations, namely “auditing”, “benchmarking”, “explainability and interpretability”, and “confidence and trust”. System components such as data validity are regularly checked by auditors. On the other hand, benchmarking in ML is the act of evaluating cutting-edge methods against tried-and-true approaches or databases for the same function (Baird & Schuller,2020). Explainability and interpretability are often brought to the center of the AI ethical debate. These concepts are associated with the requirement to comprehend how algorithms make decisions (Baird & Schuller,2020).

2.2.2. Trust in AI Outcomes

Aside from legal, ethical, organizational, or even personal factors, there may be technological challenges with the algorithm development process. Examples include the unavailability of high-quality images and labelled data, as well as the absence of external

validation inhibiting algorithm generalization (Willemink et al., 2020; Geis et al., 2019). At this time, it's unclear if the medical imaging sector as a whole is aware of these pitfalls (Huisman et al., 2021b). As shown in the second part of the study by Huisman et al. (2021), which is considered to be the largest survey previously conducted on AI adoption among radiologists, only 28% (n = 287) of respondents identified the lack of high-quality labels as a potential barrier. This may imply a relative unawareness among experts in the radiology sector

The topics of trust and the “black box” nature of machine learning are among the significant concepts that directly impact the accountability of AI results. Overall, there has always been skepticism about entirely autonomous outcomes, and many respondents believe that radiology professionals will still need to be present for safety and quality checks. Deep learning's "black box" nature inherently raises doubts about the reliability and validity of AI outcomes (Santomartino & Yi, 2022). Since radiology professionals would only utilize AI solutions if they were confident in their outcomes, trust in AI is a problem of particular importance. In the study conducted by Jungmann et al. (2020) while evaluating the attitudes toward AI Among radiologists, IT specialists, and industry representatives, less than 25% of the participants agreed that the outcomes of AI solutions can be trusted. This highlights the importance of conducting plausibility checks; AI systems' judgements must be clear and understandable. This also backs up the assertion made in the joint European-North American multi-society statement that users of AI must be able to describe how a solution uses AI to make a clinical decision (Geis et al., 2019)

There are three key components of trust in AI: the technology itself; the designers and organizations responsible for its creation, implementation, and usage; and the socio-technical systems involved in AI's life cycle (HLEG, 2019, as cited in Ryan, 2020). Although AI fulfills

every criterion in the logical explanation of trust, this is not a form of trust but rather a reliance. Even if AI makes judgments that harm an individual, it cannot be stated that AI violated the user's trust; rather, the developers or users violated this trust by failing to put in place sufficient safeguards to prevent this from happening. Because of this, stakeholders involved in creating, implementing, and utilizing reliable AI have an obligation toward its success. In general, those who support AI ethics should drop the "trustworthy AI" paradigm and switch to the "reliable AI approach" and the field should focus more on making sure that organizations and individuals who utilize AI applications are trustworthy (Ryan, 2020).

2.3. AI Governance

According to Ho et al. (2019), digital governance refers to the process of creating and implementing policies, standards and procedures put into effect for the correct establishment, use, and control of the infosphere (information environment). Digital governance relates to digital regulation; however, it is not identical to it. A set of regulations developed and implemented by social and political organizations to control different behaviours in the infosphere is known as digital regulation. In general, digital ethics, which is concerned with moral issues connected to data and information, algorithms, and infrastructures, may shape governance and regulation. (Ho et al., 2019).

The governance strategy will only succeed if it fosters trust and is trustworthy (Ho et al., 2019). This will demand a much deeper integration of ethics, law, and good practices. (Salerno et al., 2017). In accordance with applicable laws and regulations, a data governance structure will also be necessary to monitor the standards of data and quality anticipated, how data are internally

managed, how data are received, how data are safeguarded, and how data are communicated externally to various stakeholders (Loh, 2018). Aside from how AI systems function, AI governance is substantially shaped by how AI systems are perceived and imagined (Elish & Boyd, 2017, as cited in Cath, 2018). To foster public confidence in AI governance, governments, advocacy groups, and other national and international organizations are developing standards and codes of ethics (Kerasidou et al., 2021). The main scope of governance in the digital world is not only the rules of specific tools but also the challenges presented by a new toolbox. Big data, sophisticated processing tools, and algorithms are all part of that toolbox, and they are what fuel ML in all its aspects. Given this, the fundamental governance questions revolve around how we use AI and for what purposes? What are the risks and benefits? And who benefits from the use of AI? Another concern in governing AI is "how to govern AI?" as it is important to consider which public institutions are most suited for regulation and governance (Zysman & Nitzberg, 2020). Clinicians in general, and radiologists in particular, will have more ethical, legal, and societal obligations in "big data" and AI-based biomedicine to ensure that AI-related technologies are correctly interpreted, developed, and implemented (Ho et al., 2019).

One of the main objectives of governance is to maintain confidence and trustworthiness. This is essential for encouraging cooperation among all stakeholders and ensuring the ethical development and application of AI in radiology and other healthcare settings (Ho et al., 2019)

It is highly suggested that a clinical governance committee be formed with the necessary knowledge and expertise to supervise the implementation of AI models in clinical practice. Therefore, such a committee should include healthcare practitioners; managers; patient representatives; ethics and technical experts such that relevant discussions about the

effectiveness of the AI models be undertaken in addition to the regulation of privacy, safety, quality, and ethical issues (Reddy et al.,2019).

2.4. AI Infrastructure and Data Privacy

When planning to adopt new technologies, organizational factors can be just as important as individual aspects. Experts frequently report cost-effectiveness; workflow integration; ethical and legal issues; and integration as barriers to AI adoption. However, the implementation challenges anticipated by members of the radiology community, including non-AI professionals, may be comparable, but so far remain unknown (Huisman et al.,2021). The AI research community has started examining data infrastructure management more democratically, after discovering that decentralized infrastructure makes data more accessible. (Baird & Schuller, 2020). Although centralized data storage might be effective and advantageous to the "central" organization to whom the infrastructure belongs, research has shown that centralized infrastructures restrict the access and information that data providers acquire (Baird & Schuller, 2020). On the other side, given that centralized servers manage and control all the shared information, surveillance may remain a serious danger to individuals' privacy (De Filippi, 2016). As an alternative to centralized data storage, experts have extensively recommended a decentralized networking structure since it makes individual data easier to safeguard (Baird & Schuller, 2020) and provide individuals with more control over how their data is used (Kahani & Beadle, 1997). In decentralized networks, the flow of information is not managed by only a single central entity, therefore, surveillance is more challenging to implement (De Filippi, 2016). Although decentralized infrastructures may protect user privacy and help in giving users more

sense of autonomy, some degree of transparency will be required to coordinate the operations of a large network of users (De Filippi, 2016). To partially address patient data privacy, the European Union adopted GDPR (The European Commission, 2018). The main objective of the GDPR legislation is to safeguard the use of personal information by third parties. In fact, GDPR required organizations to re-ask for data consent in a more transparent manner and the "terms of agreement" certificate still serves as the foundation (Deloitte, 2016).

2.5. Review of Existing User Technology Perception / Acceptance Models

At the organizational and individual levels, the acceptance and use of information technologies can lead to both short-term and long-term benefits, such as enhanced precision in performance, improved cost and time efficiency, and escalated convenience (Curley, 1984; Sharda et al.,1988). These benefits have been acknowledged and adopted by the healthcare sector as well. Recent years have seen a rapid spread of Information Technology (IT) in healthcare, increasing the involvement of government, patients, and healthcare professionals. The ability of technology to provide benefits has always motivated Information System (IS) management studies to investigate individuals' willingness in order to embrace innovative technologies (Davis, 1989). Over the past ten years, a number of models examining "technology acceptance" have been created, and they have shown success for a "wide spectrum of IT systems" (Upadhyay et al., 2022). The available studies indicate that although technical issues with infrastructure and datasets normally serve as a significant barrier, however, the challenges relative to AI adoption in radiology are not limited to them (Lehne et al., 2019; Singh et al., 2020, as cited in Chen et al.,2021). Instead, these challenges relate to the behavioural and human aspects as well as the

requirement for related adjustments to work procedures to allow for the AI acceptance and eventually adoption of AI applications (Kelly et al., 2019 as cited in Chen et al.,2021). In fact, it has been suggested that the behaviour of healthcare professionals poses the biggest AI acceptance and adoption challenges rather than a lack of data or analytics, (Emanuel & Wachter, 2019, as cited in Chen et al., 2021). As a result, the researcher of this thesis intended to examine how radiology professionals perceive advanced technology such as AI through a theoretical lens that emphasizes on behavioural aspects of individuals and the usefulness of the technology itself.

For a considerable time, research has examined the factors impacting individuals' adoption of new technologies as well as “how” individuals perceived using technology and “why” individuals start to adopt new technologies (Venkatesh et al., 2003). within this broad field of study, several distinct research streams have been identified. Several theoretical models have been primarily developed to explain technology acceptance and use, many of which are based on psychological and sociological theories (Venkatesh et al., 2003). As argued by Dwivedi et al. (2017), some research streams significantly have focused on the technology acceptance by individuals and have considered “using intention” or “usage” as a dependent variable (Compeau & Higgins, 1995a; Davis et al., 1989). In contrast, other research streams have evaluated “satisfaction” or “net benefits” as indicators of information system success at the enterprise level (Leonard-Barton & Deschamps, 1988), or to assess task-technology fit (Goodhue, 1995; Goodhue & Thompson, 1995). Although each of these research streams contributes significantly to the literature on users' acceptance of information technology, the theoretical models that will be examined in this research study will mainly focus on the AI perceived usefulness as the primary dependent variable. Therefore, only theoretical models that considered constructs such

as technology's perceived usefulness or other constructs that can account for the radiology professionals' AI perceived usefulness will be considered. Some of these models of information technology adoption along with their associated constructs are presented in Table 1.

Table 1: Theories, Models, and Constructs of Individual Acceptance

Model /Theory	Core Constructs	Source(s)
TRA	Attitude	Fishbein and Ajzen (1975)
	Subjective Norm	
TAM	Perceived Usefulness	Davis (1989), Davis et al. (1989)
	Perceived Ease of Use	
DTPB	Attitude	Adapted from TRA/TAM
	Perceived Behavioral Control	Adapted from TPB
	Subjective Norm	
	Perceived Ease of Use	Adapted from TAM
	Perceived Usefulness	
	Compatibility	Taylor and Todd (1995b)
	Resource Facilitating Conditions	
	Technology Facilitating Conditions	
	Self-Efficacy	Taylor and Todd (1995b), Compeau and Higgins (1995a), Compeau and Higgins (1995b)
TTF	Task characteristics,	Goodhue & Thompson (1995)
	Technology characteristics,	
	Task-technology fit	
	Technology utilisation	
	Performance impact	

Note. TRA: Theory of Reasoned Action, TAM: Technology Acceptance Model, TBP: Theory of Planned Behavior, DTPB: Decomposed Theory of Planned Behavior, TTF: Task-Technology Fit Model. (Table is partially adopted from "An Empirical Validation of a Unified Model of Electronic Government Adoption (UMEGA)", by Dwivedi YK, Rana NP, Janssen M et al (2017). Government Information Quarterly. 34(2): 211-230)

As argued by Dwivedi et al. (2017), the Theory of Reasoned Action (TRA), which originates from social psychology, is considered as a highly influential theory of human

behaviour. It is commonly used as a model to anticipate behavioural intention and/or behaviour (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975). Fishbein and Ajzen (1975) classify belief antecedent into two essentially distinct categories: behavioural and normative where behavioural beliefs are thought to determine an individual's attitude towards conducting a behaviour, whereas normative beliefs impact the individuals' perception of social norms pertaining to the behaviour.

According to Fishbein and Ajzen's (1975, as cited in Dwivedi et al., 2017), an individual's positive or negative feelings about performing a specific behaviour are defined as an "attitude". An individual's attitude refers to their favourable or unfavourable emotions regarding performing a specific behaviour, while the subjective norm refers to their belief about whether or not important people in their lives believe they should or should not engage in a specific behaviour (Fishbein & Ajzen, 1975). As a result, persuasive beliefs or knowledge can influence an individual's intentions and subsequent behaviour either via their attitude or through subjective norms (Dwivedi et al., 2017).

In comparison to earlier theories, according to Kanimozhi and Selvarani (2019), the Decomposed Theory of Planned Behavior (DTPB) proposes that an individuals' actual behaviour is determined by their intention to use, which is impacted by their attitude towards the behaviour, subjective norms, and perceived behavioural control. DTPB is an extension of the Theory of Planned Behavior (TPB) that was originally developed by Taylor and Todd (1995) through breaking down the structures of attitude, subjective norms, and perceived behavioural control (Luarn & Lin, 2005). This breakdown enhanced the ability of the model to accurately comprehend and explain behavioural intentions (Pedersen, 2005). DTPB takes TPB a step further by decomposing beliefs towards behavioural intention antecedents. The decomposition of the

beliefs into multidimensional constructs reflects a wide range of dimensions that are consistently linked to the antecedents of intention and help to define the relationship between the antecedents of behaviour (Kanimozhi & Selvarani, 2019). The DTPB offers many of the advantages that are associated with the Technology Acceptance Model (TAM). However, it is more complicated than the TAM because it includes a significant number of variables that might impact technology usage (Dwivedi et al., 2017).

Even though the TRA and DTPB theories both cover the concept of the perceived usefulness of technology, they both contain subjective norms as a key construct. According to a number of research studies including Dishaw and Strong (1999) examining IT utilization, the evidence shows that subjective norms are not an important factor to be considered when evaluating individuals' use of IT. On the other hand, since the subjective norm is not relevant to the thesis research question, survey design and research objectives considered for this thesis, the researcher intended to exclude both theories from the current study. The primary focus of this study will mainly be on the TAM and TTF models, which will be explained in detail in the following sections.

2.5.1. Technology Acceptance Model (TAM)

The perception of technology by healthcare professionals can be explained by a number of theoretical frameworks. These include the Technology Acceptance Model (TAM), which emphasizes the importance of perceived usefulness and ease of use in anticipating the intention of users to utilize technology. In fact, in order to overcome the limitations that are associated with the absence of a theoretical model and measurement scales to assess technology acceptance,

Davis (1989) created the TAM based on the TRA framework (Marikyan & Papagiannidis, 2022). According to Davis (1989), the fundamental idea behind the development of TAM was that behavioural intentions were shaped by particular beliefs concerning the use of technology rather than a generic attitude towards behavioural intention. TAM was established primarily to provide insights into the mechanisms that drive users' technology acceptance with the aim of anticipating individuals' behaviour and providing a theoretical basis for the effective implementation of technology. In practical terms, TAM aimed to guide practitioners in taking appropriate measures before integrating technology systems (Marikyan & Papagiannidis, 2022).

The two main TAM's constructs are "Perceived Usefulness" and "Perceived Ease of Use". As argued by Marikyan and Papagiannidis (2022), based on the previous empirical studies on human behaviour and information system management, multi-item scales for measuring "Perceived Usefulness" and "Perceived Ease of Use" were developed, pre-tested, and validated in a number of research studies. It was hypothesized that these two constructs were essential predictors of users' acceptance of technology, as suggested by previous research (Johnson & Payne, 1985; Payne, 1982; Robey, 1979).

As suggested by a number of research studies, the decision to engage in a particular behaviour is based on individuals' evaluation of the advantages they expect to get from the behaviour in relation to the effort and/or costs involved in performing it (Johnson & Payne, 1985; Payne,1982). As explained by Davis (1989) the use of an information system is impacted by the trade-offs between the system's perceived usefulness and the perceived level of difficulty that is associated with using that particular system. In other words, individuals assess the value of utilizing a system by evaluating its usefulness against the perceived challenges of using it.

With reference to the claim of Davis (1989), “Perceived Usefulness” is defined as *“the individual's perception of the extent to which the use of a given technology improves performance”* (Marikyan & Papagiannidis, 2022, p.2), and “Perceived Ease of Use”, on the other hand, is defined as *“the degree to which a person believes that using a particular system is free of effort”* (Marikyan & Papagiannidis, 2022, p.2). It has been also claimed by Marikyan and Papagiannidis (2022) that the concept of “Perceived Ease of Use” is similar to the idea of the "complexity factor" that is theorized in the innovation diffusion literature, and it can serve as a barrier to the adoption of innovation.

As argued by Davis (1989), TAM proposes that the acceptance of technology occurs in a three-stage process in which external factors, such as system design features, elicit cognitive reactions like perceived usefulness and ease of use. These reactions then create an affective response, which shapes the attitude toward utilizing technology and the intention to do so, ultimately impacting the user's behaviour. Therefore, TAM as a model predicts behaviour based on three main components: perceived ease of use, perceived usefulness, and behavioural intention (Marikyan & Papagiannidis, 2022). In fact, as argued by Park and Park (2020), according to the TAM, perceived usefulness and ease of use are the primary factors that influence the attitude individuals have toward technology. This model only takes into account the relationships among belief, attitude, intention, and behaviour and assumes that all external factors influence intention and attitude indirectly via perceived usefulness and ease of use. The constructs in the tested TAM framework are illustrated in Figure 1.

According to Davis (1993), “Perceived Usefulness” has a direct effect on actual use, emphasizing its significant role in predicting behaviour. While “Perceive Ease of Use” does

not have a direct influence on usage behaviour, it plays a foundational role in the impact of "Perceived Usefulness". This model suggests that if an application is expected to be user-friendly, it is more likely to be considered as a valuable application by the user and hence more likely to stimulate technology acceptance (Davis,1989; Davis,1993). As argued by Marikyan and Papagiannidis (2022), the development of TAM and associated measures have always had noteworthy theoretical contributions and practical benefits. The model's ability to test the usability of the information system made it possible to assess the users' motivation to adopt various technologies (Hwang, 2005; Gefen et al., 2003; Araujo & Casais, 2020) which was not feasible previously due to the lack of established subjective metrics. For almost thirty years, it has been shown that TAM is theoretically robust and has strong predictive capability in assessing individuals' intention to use technology (Marikyan & Papagiannidis, 2022). As argued by Marikyan and Papagiannidis (2022), TAM and its extensions have found application in numerous domains, contexts, and geographies, serving as an important theoretical tool for anticipating user's behaviour. TAM was evaluated in diverse contexts such as healthcare institutions, agriculture, and natural resources utilization (Arkesteijn & Oerlemans, 2005; Flett et al., 2004; Kummer et al., 2013). However, according to Hu et al. (1999), when evaluating the telemedicine technology adoption among physicians, the intention of healthcare professionals to use the technology was determined solely by "Perceived Usefulness". These results can be interpreted in two ways: the impact of "Perceived Ease of Use" on technology adoption is diminished when 1) the technology has a lower functional value, and 2) the study involves particular categories or groups of users possessing specific skills required for technology use (Marikyan & Papagiannidis, 2022). On the other hand, as argued by Rouidi et al. (2022), TAM is

among the most frequently utilized models and theories to predict acceptance behaviour in healthcare settings. In a systematic review conducted by Harst et al. (2019) that aimed to identify the theories and models which have been used by researchers to predict telemedicine acceptance behaviour, out of the 24 eligible studies included in this review, 11(45.83%) used TAM. In addition, among the 119 eligible studies included in the systematic review conducted by Heinsch et al.(2021) that intended to identify the theories and models used to examine the implementation of e-health, 33 (27.73%) studies used TAM (illustrated in Figure 1) to evaluate e-health implementation.

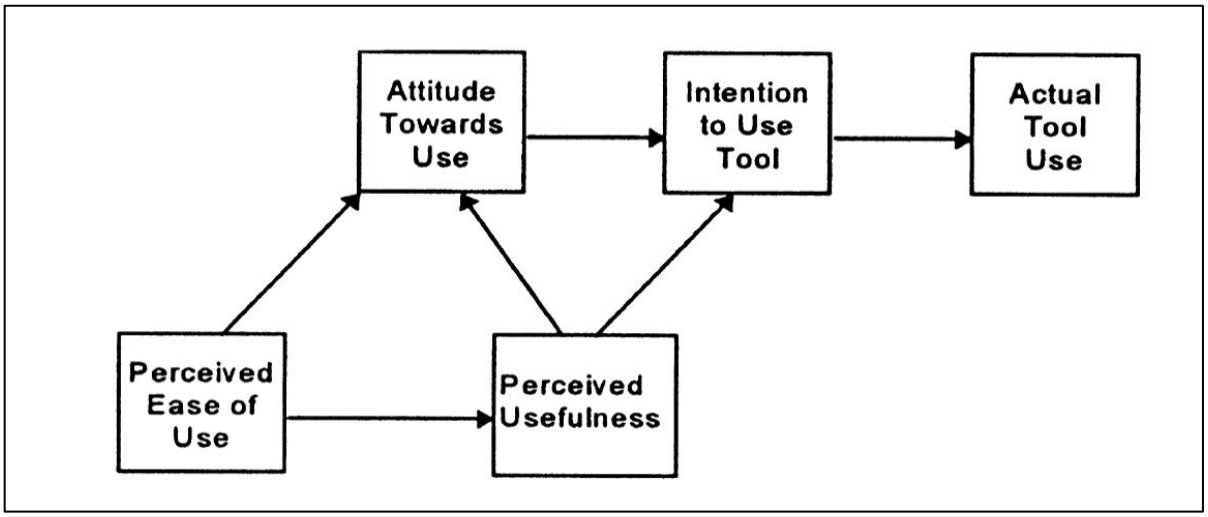

Figure 1: Technology Acceptance Model (TAM) by Devis (1989)
Note: Figure is adopted from "Extending the technology acceptance model with task-technology fit constructs" Dishaw, M. T., & Strong, D. M. (1999). Information & Management, 36(1), 9–21

2.5.2. Task-Technology Fit (TTF) Model

The incapacity of TAM in comprehending IT usage often lies in its failure to focus on tasks. Users utilize IT as a tool for completing organizational tasks. The absence of a task-

oriented approach in assessing IT and its acceptance, usage, and performance may lead to inconsistent results in IT evaluations (Goodhue & Thompson, 1995). Although the concept of usefulness in TAM is inherently associated with tasks, the explicit inclusion of task-related aspects may result in a more effective model of IT utilization. This issue can be effectively addressed by the task-technology fit (TTF) perspective (Dishaw & Strong, 1999).TTF refers to the correlation that exists among the characteristics of an individual (who utilizes technology), technology (including data, software tools, hardware, and technology services), and task (an activity performed by individuals in order to achieve the desired output) (Marikyan & Papagiannidis,2022b). The concept of TTF represents the extent to which information technology (IT) can help in task completion, where the capabilities of the technology should be aligned with the task's requirements. This is a formal framework that is used for expressing the level of assistance that IT can provide (Goodhue & Thompson, 1995). According to TTF, the utilization of IT is dependent on whether its functions that are made available for the user are suitable for supporting (Fitting) the user's activities. In other words, IT will only be used if its functions are in alignment with the user's needs. Therefore, information technology will not be used if it does not deliver sufficient benefits or advantages (Dishaw & Strong, 1999). As argued by Dishaw & Strong (1999), while TTF is a recent addition to the Management Information Systems (MIS) literature, the idea of fit or correspondence is a well-established concept in organizational theories such as the theory of work adjustment, which serve as the foundation of TTF model. The theory of work adjustment takes into consideration the match between an individual's abilities and the job's required skills in determining the satisfactoriness of individuals for the job (Goodhue & Thompson, 1995). Additionally, research on strategic fit, which focuses

on the match between an organization and its environment, has impacted the methods used to calculate TTF (Dishaw & Strong, 1998; Goodhue, 1995; Venkatraman, 1989).

The research studies considered systems implementation have acknowledged the importance of having a suitable fit between technologies, tasks, and users (Palvia & Chervany, 1995). Several data quality research highlighted the importance of ensuring that data fit the needs of user tasks (Dishaw & Strong, 1998; Strong, 1997; Strong et al., 1997). The concept of "cognitive fit" which has emerged from research on problem-solving and problem representation, states that problem-solving operates ideally when the problem representation, as well as any tools or aids, all support the processes needed to complete the task (Vessey & Galletta, 1991). According to Goodhue (1998), the TTF model has various dimensions to evaluate how well technology fits the tasks performed. These dimensions include ease of use; accuracy; currency; compatibility; meaning; reliability of the system; accessibility; level of detail; assistance and support; presentation; locatability; level of detail; and clarity or lack of confusion. As argued by Marikyan and Papagiannidis (2022b), the TTF model presented a conceptual framework for examining a number of technology performance issues. These issues cover a broad range of topics, such as evaluating the success of information systems management, investigating the significance of individuals' involvement with technology and how it influences performance, and employing the TTF model to identify issues related to information system utilization (Goodhue & Thompson, 1995). The TTF framework has acquired widespread acceptance among researchers, resulting in its extensive application in investigating technology utilization and adoption (Lin, 2012; Wu & Chen, 2017; Lin & Huang, 2008). Since its original proposal, the TTF has been extensively studied and implemented in a variety of

fields, including healthcare. One of the applications of the TTF model was to assess the performance and efficiency of information systems in hospitals (Chen et al., 2015). The study conducted by Karsh et al. (2009), aimed to investigate whether the technology perception nurses have could affect the quality of care they provide at both individual and unit levels, shows that nurses' self-efficacy in utilizing technology and their perception of their abilities to provide quality care relate to several “fitting” aspects, including technology usefulness, ease of use, and compatibility with work style of the healthcare providers.

When it comes to the application of TTF framework, as argued by Marikyan and Papagiannidis (2022b), the studies that have validated the TTF and its extensions have shown that the impact of variables varies due to differences in cultures, beliefs, values, and work attitudes. For example, a study that assessed how technology fits into managerial tasks in Greece and the United States discovered that the two groups distinguish between various TTF dimensions. These findings led the researchers to conclude that managers perform tasks and engage with technology in distinct ways in different countries (Ferratt & Vlahos, 1998).

Figure 2 presents the TTF model tested by Dishaw & Strong (1999), where the level of tool experience, which indicates an individual's abilities, is expected to have a direct effect on actual tool utilization. In the current research, the researcher is mainly focusing on direct relations only (non-doted lines). Although the TAM and TTF frameworks have been used by many studies and are advantageous on their own, research has demonstrated that the integrated model of TAM/TTF offers a more reliable explanation when it comes to the individual's technology utilization than either model alone. According to Dishaw and Strong (1999), the TAM/TTF integrated model provides a more comprehensive explanation for the IT utilization

variance compared to either the TAM or TTF models alone. In fact, through an empirical validation comparing the TAM, TTF, and integrated TAM/TTF theories, Dishaw and Strong (1999) showed that the TAM/TTF integrated model is capable of explaining 51% of the variance in the utilization construct. In contrast, if the TAM and TTF models were examined separately, they could only explain 36% and 41% of the variance respectively. With the support of the mentioned arguments, the researcher of this thesis considered the TAM/TTF integrated framework to evaluate how radiology professionals perceive AI applications. By considering a reliable model like the integrated model of TAM/TTF with the ability to explain a good percentage of variance in individuals' technology utilization, the researcher ensures the trustworthiness of the study to contribute to the available research on identifying the variables influencing radiology professionals' perceptions of AI applications' usefulness.

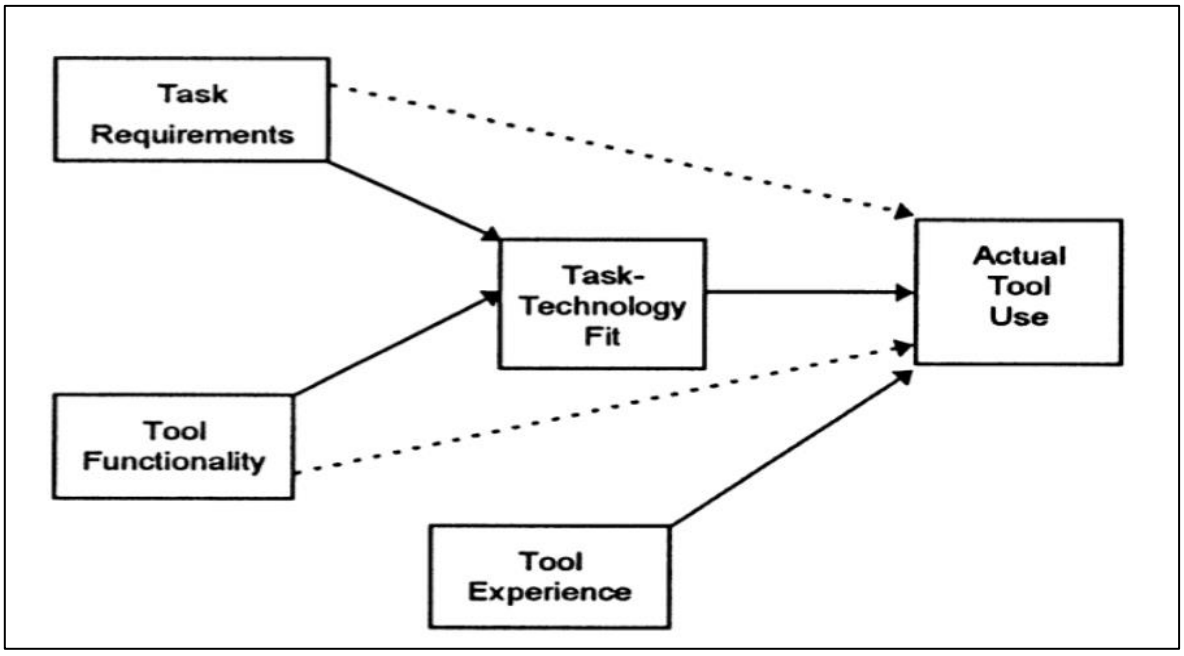

Figure 2: Task-Technology Fit (TTF) Model by Goodhue & Thompson (1995).
Note: Figure is adopted from "Extending the technology acceptance model with task-technology fit constructs" Dishaw, M. T., & Strong, D. M. (1999). Information & Management, 36(1), 9–21

2.6. Research Gap

Despite the growing interest among researchers in conducting studies assessing the adoption of AI in the healthcare sector, there are a limited number of studies specifically evaluating the perception of radiology professionals toward AI applications in radiology settings. Furthermore, most of these studies were reviews rather than proposing a reliable theoretical framework. Therefore, the most significant gap that this thesis aims to address is to propose a theoretical framework that can explain radiology professionals' perceived usefulness of AI applications in radiology settings. Although there are a few studies that evaluated the perception of radiology professionals toward AI applications' usefulness in medical imaging, however, to the best of the researcher's knowledge none of these studies considered TAM/TTF integrated model for the same purpose.

3. Material and Methods

A major part of this study is dedicated to the analysis of the data collected through a cross-sectional survey administered in May 2020 by Abuzaid et al. (2020). This survey was distributed among radiology professionals (Radiographers and Radiologists) located in the United Arab Emirates (UAE). Given the record of the radiology population in the UAE, the sample size of 272 was identified as the survey research project target. However, only 153 individuals participated and responded to the survey, reflecting a response rate of 56.3% of the identified population as reported by Abuzaid et al. (2020). Given the ethical aspects associated with the use of the secondary dataset provided by the initial researcher, the dataset related to only 119 participants has been provided for this study. In general, the survey gathered data on the

participants' demographics, work experience, and educational backgrounds. The questionnaire was designed to best examine the participant's understanding, perceptions, organization readiness, and AI integration challenges in the radiology context from the radiology professional's perspective.

3.1. Ethical Approval

The survey was approved by the University of Sharjah's research ethics committee. According to Abuzaid et al. (2020), all the techniques and procedures were carried out in accordance with the rules and regulations established by the study ethics committee (reference number REC-20-05- 06-01). The participants gave their consent through an online form, and the research was carried out in accordance with the Declaration of Helsinki. As part of the thesis requirements, this study also obtained approval from the Research Ethics Board (REB) of Toronto Metropolitan University (see Appendix A).

3.2. Data Collection

Two major sections made up the original survey: 1) data on the participants' demographics, including age, gender, education, and clinical expertise, 2) data on the participants concerning the integration of AI into radiology settings, the participants' expertise, perceptions, organizational readiness, and challenges were recorded in the second part of the survey. Since the online survey employs an anonymous function, no personal information was gathered. Due to ethical considerations, the researcher of this thesis has access only to the numerical datasheet of the survey provided by the initial researcher.

3.3. Participant Demographics

Out of 119 radiology professionals, 47 (39.50%) were female and 72 (60.50%) were male. Generally, participants were mainly young with the majority aged between 25-34 years old (52, 43.70%), followed by 35-44 years old (35, 29.41%). Only 5 out of 119 respondents (4.20%) were more than 55 years of age. Regardless of gender, the majority of participants had a bachelor's degree (94, 78.99%), followed by a master's degree (14, 11.76%) and a diploma (11, 9.24%). In general, male participants had a higher level of education compared to their female counterparts. When it comes to the years of medical imaging experience, the survey results show that more than half of the participants (70, 58.82%) had 5-20 years of experience, with a greater percentage of male participants (56, 47.06% of all participants). A considerable proportion of female participants (28, 23.53% of all participants) had less than 5 years of experience in medical imaging, while there were only 4 (3.36%) participants with over 30 years of experience, all of whom were male. Table 2 and Figures 3, 4, and 5 provide detailed information on the participants' demographics.

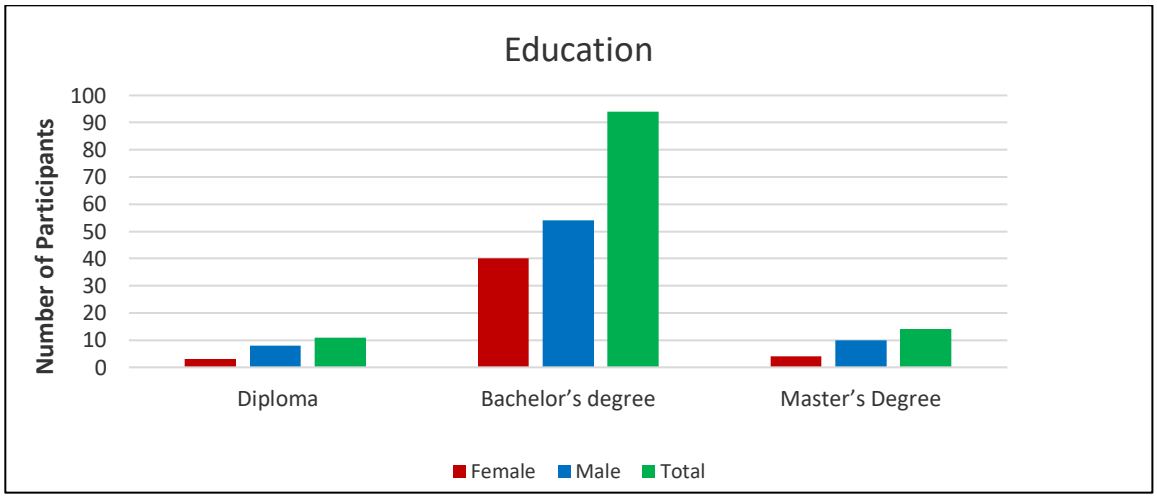

Figure 3: Educational Demographics of Survey Participants

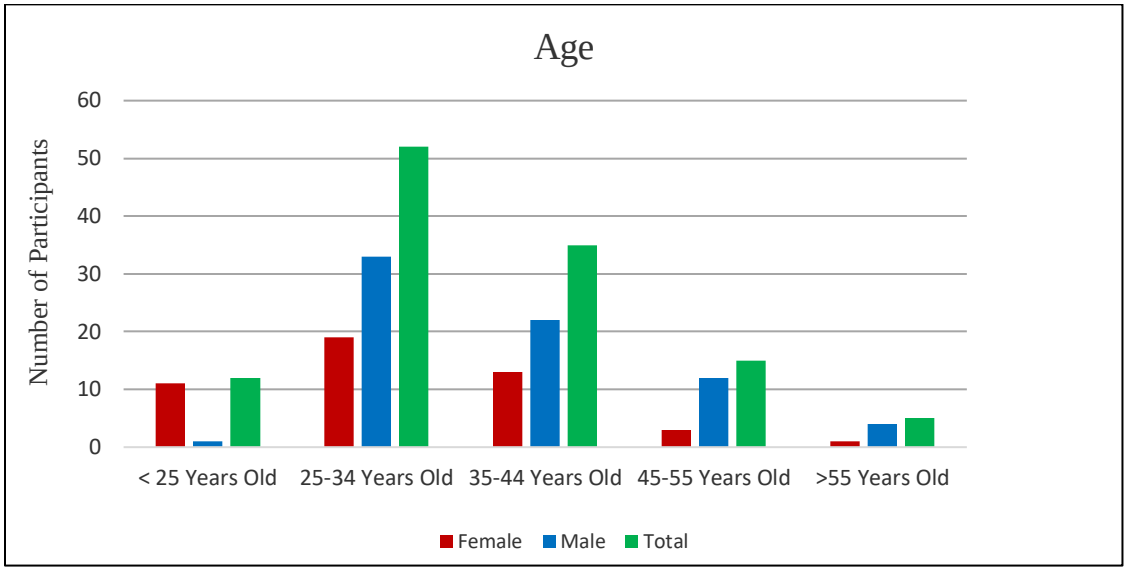

Figure 4: Age Distribution of Survey Participants

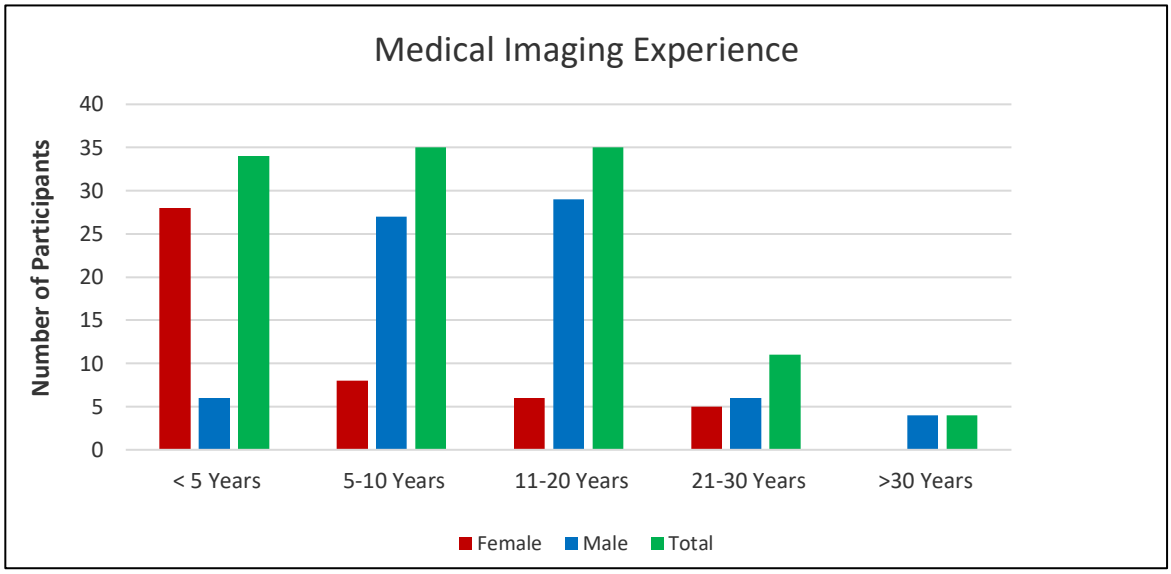

Figure 5: Medical Imaging Experience of Survey Participants

Table 2: Demographic Characteristics of Participants

Categories	**Female** (n, %)	**Male** (n, %)	**Total** (n, %)
Gender	47 (39.50%)	72 (60.50%)	119 (100%)
Age			
< 25 Years Old	11 (9.24%)	1 (0.84%)	12 (10.08%)
25-34 Years Old	19 (15.97%)	33 (27.73%)	52 (43.70%)
35-44 Years Old	13 (10.92%)	22 (18.49%)	35 (29.41%)
45-55 Years Old	3 (2.52%)	12 (10.08%)	15 (12.60%)
>55 Years Old	1 (0.84%)	4 (3.36%)	5 (4.20%)
Education			
Diploma	3 (2.52%)	8 (6.72%)	11 (9.24%)
Bachelor's degree	40 (33.61%)	54 (45.38%)	94 (78.99%)
Master's Degree	4 (3.36%)	10 (8.40%)	14 (11.76%)
Origin of Qualification			
Europe	5 (4.20%)	13 (10.92%)	18 (15.12%)
Africa	14 (11.76%)	22 (18.49%)	36 (30.25%)
Asia	12 (10.08%)	21 (17.65%)	33 (27.73%)
Middle East	16 (13.45%)	15 (12.60%)	31 (26.05%)
Others	N/A	1 (0.84%)	1 (0.84%)
Medical imaging Experience			
< 5 Years	28 (23.53%)	6 (5.04%)	34 (28.57%)
5-10 Years	8 (6.72%)	27 (22.69%)	35 (29.41%)
11-20 Years	6 (5.04%)	29 (24.37%)	35 (29.41%)
21-30 Years	5 (4.20%)	6 (5.04%)	11 (9.24%)
>30 Years	N/A	4 (3.36%)	4 (3.36%)

Note. The % represents the percentage value out of the total number of participants (n=119)
N/A represents the non-applicable option

3.4. Participants' AI Perception Analysis

The participants' perceptions towards the implementation of AI in radiology practices have been assessed in the survey by measuring their level of agreement with four main statements on a Likert scale of 1 to 5 (Strongly disagree to strongly agree). The statements were

as follows: 1) *AI will play an important role in the practice of radiology professionals*, 2) *AI will be used in many applications and image production, such as quality control, dose selection, and image interpretation*, 3) *AI will threaten or disrupt the practice of radiology professionals*, 4) *AI will threaten or disrupt some radiology professionals' careers*, 5) *AI has no limitations in my work*. Participants' perceptions toward each statement are explained in the following sections.

3.4.1. Perception of AI Role in Radiology Practices

The results of the survey show that regardless of gender, most of the participants agreed that AI plays an important role in radiology. Out of 119 participants, 57 (47.90%) participants strongly agreed, 48 (40.34%) agreed, and 12 (10.08%) were neutral. Only 2 (1.68%) out of 119 participants strongly disagreed. Breaking down the responses by gender shows that male participants had a higher percentage of strongly agreed responses compared to their female counterparts (56.94% of males vs. 34.04% of females), while female participants had a greater percentage of agreed (33.33% of males vs. 51.06% of females) and neutral (9.72% of males and 10.64% of females) responses. Further analysis of the responses by gender shows that both respondents who strongly disagreed were females too (2, 4.25%).

3.4.2. Perception of AI Applications in Radiology Practices

When it comes to the application of AI, and whether AI will be used in many applications and image production, such as quality control, dose selection, and image interpretation, the survey results show that the majority of participants perceive AI's potential in a variety of applications including image production. Most of the survey participants agreed or strongly

agreed with the statement (113, 95%). Only a small percentage of participants disagreed (2, 1.68%) and the remaining were neutral (4, 3.36%). Considering the gender breakdown of the responses, a higher percentage of male (30, 54.17%) participants strongly agreed with the statement compared to female participants (17, 36.17%), while a higher percentage of female (26, 55.32%) participants agreed with the statement compared to their male counterparts (31, 43.06%). There were also higher neutral responses among female participants compared to male participants (1.39% of males and 6.38% of females). It is also worth mentioning that there were no participants who selected the strongly disagree response.

3.4.3. Perception of AI Potential Threat in Radiology Practices

To evaluate the participants' perception about the AI implementation in radiology practices, part of survey was dedicated to assessing the participants' opinions regarding the potential threat or disruption that AI may bring to radiology practices. The survey results show that in general a considerable percentage of participants (67, 56.30%) do not believe that AI will threaten or disrupt the radiology practice, with 19 (15.97%) participants selecting either disagree or strongly disagree and 48 (40.34%) participants selecting neutral. On the other hand, 52 (43.70%) participants agreed or strongly agreed with the statement, reflecting a considerable level of concern about the possible threat or disruption of AI in radiology practice. Considering the responses by gender, there is a similarity in the percentage of male and female participants who believe that AI will threaten or disrupt the radiology practice. Out of 119 participants, 33 (45.83%) males and 19 (40.43%) females agreed or strongly agreed, while 12 (16.67%) males and 7 (14.89%) females selected disagree or strongly disagree responses. Nearly half of all

participants (48, 40.34%) were neutral about the potential disruption that AI may bring to radiology practices. Overall, it is noteworthy to mention that the participants' responses to the statement were diverse with some participants strongly feeling one way and others who were neutral. This indicates that there is a range of viewpoints among participants on the possible impact that AI may have on radiology practices.

In additional attempts to evaluate participants' perspectives on the potential threat or disruption AI may bring to radiology practices, participants were asked whether AI will threaten or disrupt the careers of some radiology professionals. The survey results show that most of the participants (77, 64.70%) agreed or strongly agreed with the statement, implying that they believe in the negative impact that AI may have on the careers of some radiology specialists. When it comes to gender, 46 (63.89%) of male participants agreed or strongly agreed with the statement, 14 (19.44%) were neutral, and 12 (16.67%) disagreed or strongly disagreed. On the other hand, among the female participants, 31(65.96%) participants agreed or strongly agreed with the statement, 9 (19.15%) were neutral, and 7 (14.89%) disagreed or strongly disagreed. Furthermore, there was more male than female participants who agreed or strongly agreed with the statement; however, when the percentages of each gender are considered, the results suggest that both categories perceive a similar percentage of the possible risk that AI may pose to the career of radiology professional.

3.4.4. Perception of AI Limitations in Radiology Practices

As part of evaluating the participants' perceptions toward the implementation of AI in the radiology department, participants were asked to provide their perception of *"AI has no*

limitations in my work". According to the survey findings, almost half of the participants agreed or strongly agreed with the statement. It appears that more male participants strongly agree with the statement of "AI has no limitations in their work" than their female counterparts. Out of 58 (48.74%) participants who agreed or strongly agreed, 35 were males (48.61% of male participants) and 23 were females (48.94% of female participants). On the other hand, out of 119 participants, 61(51.26%) selected neutral, disagree or strongly disagree responses. Among all the responses, 28 (23.53%) participants selected neutral responses, with 18 being males (25% of male participants) and 10 being females (21.28% of female participants). In general, more male participants disagreed with the statement compared to females. Out of the total of 28 (23.53%) disagree responses, 19 were males (26.39% of male participants) and 9 were females (19.15% of female participants). However, only 5 (4.20%) of all participants strongly disagreed with the statement. The percentage of participants being neutral was almost similar between male and female participants. However, all the strongly disagreed responses came from female participants (10.64% of the female participants).

Table 3 presents all the details regarding participants' perceptions of AI Implementation in the radiology department.

3.5. Participants' AI Feeling Analysis

In order to evaluate participants' general feelings towards AI technologies, participants were explicitly asked to express how they feel about AI on a five-point Likert scale, with response options including: *"Excited", "Aware of the challenges" "Neutral", "Overwhelmed, I*

Table 3: Participants' Perceptions of AI Implementation In The Radiology Department

Statements	**Female** (n=47)	**Male** (n=72)	**Total** (n=119)
AI will play an important role in the practice of radiology professionals			
Strongly Agree	16 (34.04%)	41 (56.94%)	57 (47.90%)
Agree	24 (51.06%)	24 (33.33%)	48 (40.34%)
Neutral	5(10.64%)	7 (9.72%)	12 (10.08%)
Disagree	N/A	N/A	N/A
Strongly Disagree	2 (4.26%)	N/A	2 (1.68%)
AI will be used in many applications and image production, such as quality control, dose selection, and image interpretation			
Strongly Agree	17 (36.17%)	39 (54.17%)	56 (47.06%)
Agree	26 (55.32%)	31 (43.06%)	57 (47.90%)
Neutral	3 (6.38%)	1 (1.39%)	4 (3.36%)
Disagree	1 (2.13%)	1 (1.39%)	2 (1.68%)
Strongly Disagree	N/A	N/A	N/A
AI will threaten or disrupt the practice of radiology professionals			
Strongly Agree	6 (12.77%)	12 (16.67%)	18 (15.13%)
Agree	13 (27.66%)	21 (29.17%)	34 (28.57%)
Neutral	21 (44.68%)	27 (37.50%)	48 (40.34%)
Disagree	5(10.64%)	9 (12.50%)	14 (11.76%)
Strongly Disagree	2 (4.26%)	3 (4.17%)	5 (4.20%)
AI will threaten or disrupt some radiology professionals' careers			
Strongly Agree	6 (12.77%)	19 (26.39%)	25 (21.00%)
Agree	25 (53.19%)	27 (37.50%)	52 (43.70%)
Neutral	9 (19.15%)	14 (19.44%)	23 (19.33%)
Disagree	3 (6.38%)	8 (11.11%)	11 (9.24%)
Strongly Disagree	4 (8.51%)	4 (5.55%)	8 (6.72%)
AI has no limitations in my work			
Strongly Agree	4 (8.51%)	14 (19.44%)	18 (15.13%)
Agree	19 (40.43%)	21 (29.17%)	40 (33.61%)
Neutral	10 (21.28%)	18 (25.00%)	28 (23.53%)
Disagree	9 (19.15%)	19 (26.39%)	28 (23.53%)
Strongly Disagree	5 (10.64%)	N/A	5 (4.20%)

Note. The % represents the percentage value out of the total number of each category.
N/A represents the non-responded option

don't feel I can keep up", "Worried about the impact", and *"I don't know enough".* The response options were selected in a way to represent a variety of possible users' attitudes toward AI. Participants were asked to choose the option that best reflected their feelings toward AI.

According to the survey results, regardless of gender, the most frequently selected responses were "Aware of the challenges" and "Excited" which were selected by 43 (36.13%) and 38 (31.93%) participants respectively. When it comes to gender, the most selected response among the female participants was "Aware of the challenges" which was selected by 16 (34.04%) female participants, followed by "Excited" which was selected by 10 (21.28%) female respondents, and "Neutral" response was selected by 10 (21.28%) female participants. Out of the remaining female participants, 4 (8.51%) participants selected "Worried about the impact" and 7 (14.89%) selected "I don't know enough". On the other hand, "Excited" was the most frequently selected response among the male participants which was selected by 28 (38.89%) participants followed by "Aware of the challenges" response selected by 27 (37.50%) of male participants and "Neutral" response selected by 10 (13.89%) of male participants. Out of the remaining male participants, 4 (5.56%) participants selected "Worried about the impact" and 2 (2.78%) participants selected "Overwhelmed, I don't feel I can keep up". Only one male participant selected "I don't know enough" which counts for 1.39% of male respondents. These data imply that while both gender categories of participants displayed a variety of feelings towards AI, male participants were more likely to select excitement, while female participants were more likely to report awareness of the technology challenges. Surprisingly, according to the results of the survey, only 6.72% of participants were concerned about the AI impact. Furthermore, when it comes to the knowledge of AI, female participants were more concerned than their male

counterparts (14.89% of females vs. 1.39% of males). Figure 6 and Table 4 depict the survey results related to participants' feelings about AI.

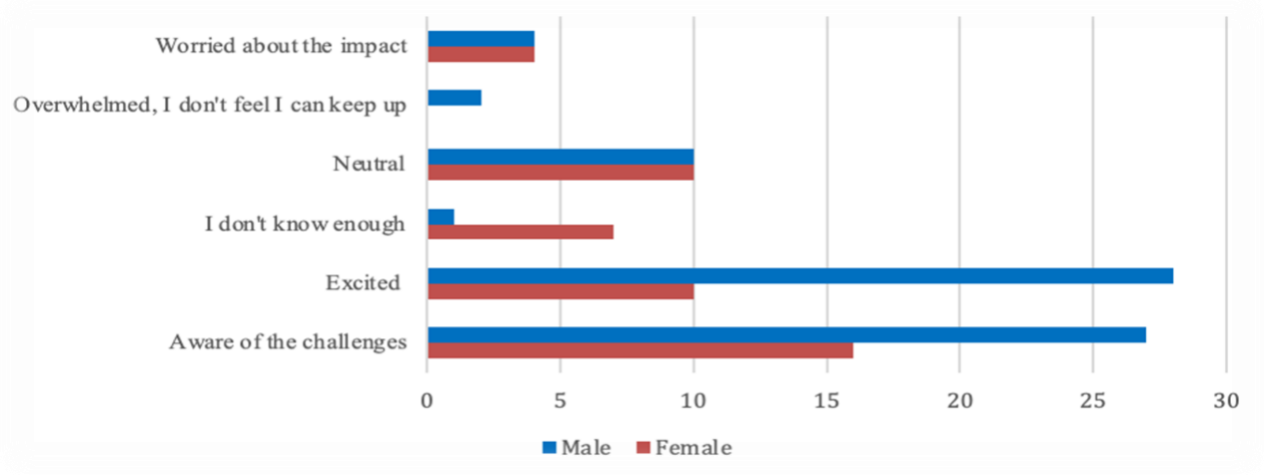

Figure 6: Participants' Feelings About AI

Table 4: Participants' Feeling About AI

Statements	**Female** (n=47)	**Male** (n=72)	**Total** (n=119)
"How do you feel about AI? "			
Aware of the challenges	16 (34.04%)	27 (37.5%)	43 (36.13%)
Excited	10 (21.28%)	28 (38.89%)	38 (31.93%)
I don't know enough	7 (14.89%)	1 (1.39%)	8 (6.72%)
Neutral	10 (21.28%)	10 (13.89%)	20 (16.81%)
Overwhelmed, I don't feel I can keep up	N/A	2 (2.78%)	2 (1.68%)
Worried about the impact	4 (8.51%)	4 (5.56%)	8 (6.72%)

Note. The % represents the percentage value out of the total number of each category
N/A represents the non-responded option

3.6. Participants' AI Working Knowledge Analysis

Throughout the survey, the AI knowledge and skills of participants were evaluated through three different sections. The first section primarily focused on the main question *"How well do you understand what is meant by AI?"*, in this section participants were requested to rate their AI familiarity on a five-point Likert scale. The response options included *"I have no idea", "Only what I have read in news, posters, or media", "I am familiar with it but would not confidently apply that knowledge at work", "I am comfortable with what it means, but I am not technical,"* and *"Very comfortable. I work in AI."*

In the second section, a set of six statements were used to evaluate participants' opinions about AI education. These statements were aimed to evaluate how strongly participants believe that AI education should be integrated in their respective academic programs. The statements were as follows: *"All radiology professions curriculum include at least some basic knowledge of AI", "AI should be taught in the undergraduate programme", "AI should be taught in the postgraduate programme", "I have a basic understanding of AI (relevant to my field)", "I have a working knowledge of AI (relevant to my field)",* and *"I have been trained and educated about AI (relevant to my field)".*Considering the statements, participants were asked to give their degree of agreement on a five-point Likert scale ranging from strongly agree to strongly disagree.

The final section of this part of the survey was dedicated to examining how participants have acquired their AI knowledge and skills. A five-point Likert scale was used asking participants to choose the approach that best describes their situations. The response options included the following options: *"Self-taught", "Attending courses", "Postgraduate training", "Work-related activities",* and *"No knowledge".*

3.6.1. Participants' General Knowledge of AI

The participants' responses to "How well do you understand what is meant by AI?" show that AI is understood differently by male and female participants. However, based on the responses, it seems that males are more comfortable with the concept of AI than females. In general, the participants demonstrated a promising level of AI knowledge, with only 10 respondents out of 119 (8.40%) indicating a lack of familiarity with the topic by selecting the "Have no idea" response. Out of which 6 were female (12.77% of female respondents) and 4 were males (5.56% of male participants). Notably, this result shows that female participants demonstrated comparatively lower levels of AI knowledge compared to male participants. On the contrary, a considerable number of participants (36, 30.25%) stated that they had only received basic knowledge of AI through sources such as news, posters, or media. Out of which 18 (38.30% of female participants) were female and 18 (25% of male participants) were male.

When it comes to participants' confidence in applying AI knowledge at work, 37(31.09%) of participants responded that they are familiar with AI but wouldn't confidently apply that knowledge at work. The majority of this category were male (26, 36.11% of male participants) while 11 were female (23.40%). Similar to the group of participants with basic AI knowledge, 36 out of 119 participants (30.25%) reported being either "Very comfortable and working in AI" or "comfortable with what AI means, but not being technical." The percentage of male participants in this category (33.33%) was greater than that of female participants (25.53%). The survey results of participants' general AI knowledge have been summarized in Table 5 and Figure 7 as illustrated below.

Table 5: Participants' General Knowledge of AI

Statements	**Female** (n=47)	**Male** (n=72)	**Total** (n=119)
"How well do you understand what is meant by AI?"			
Have no idea	6 (12.77%)	4 (5.56%)	10 (8.40%)
Only what I have read in news, posters, or media	18 (38.30%)	18 (25%)	36 (30.25%)
I'm familiar with it but wouldn't confidently apply that knowledge at work	11(23.40%)	26 (36.11%)	37 (31.09%)
I'm comfortable with what it means, but I am not technical	9 (19.15%)	12 (16.67%)	21 (17.65%)
Very comfortable. I work in AI	3 (6.38%)	12 (16.67%)	15 (12.60%)

Note. The % represents the percentage value out of the total number of each category
N/A represents the non-responded option

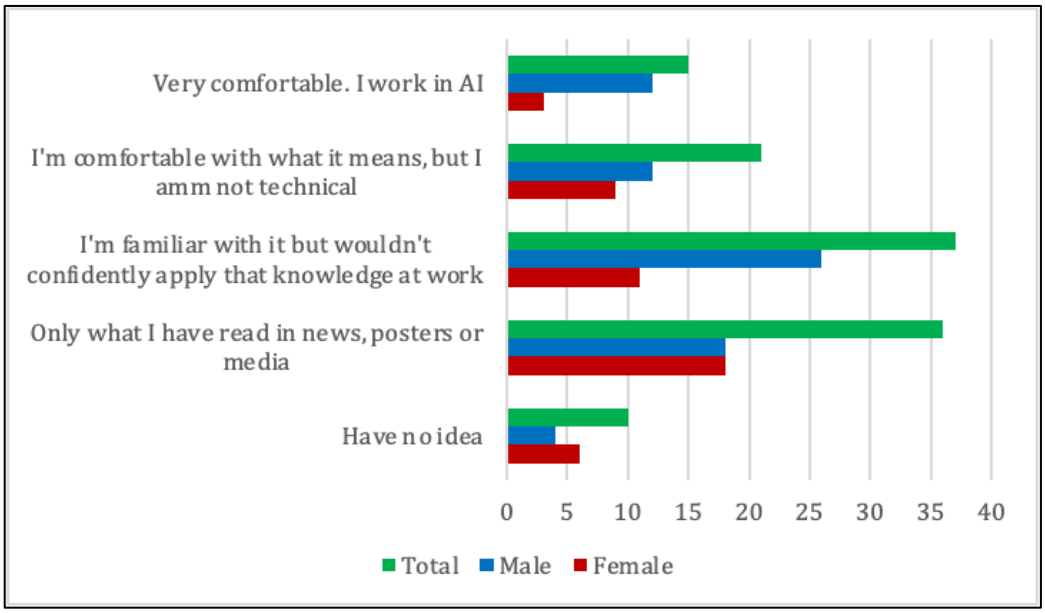

Figure 7: Participants' General Knowledge of AI

3.6.2. Participant's Perception of AI Education and Experience

In order to evaluate participants' perceptions about the integration of AI education within university curricula, the survey dedicated part to assessing participants' perception towards following statements, including: *"All radiology professions curriculum includes at least some basic knowledge of AI", "AI should be taught in the undergraduate programme",* and *"AI should be taught in the postgraduate programme".* Also, the survey included statements intended to measure participants' current level of AI knowledge and experience. These statements included: *"I have a basic understanding of AI (relevant to my field)", "I have a working knowledge of AI (relevant to my field)",* and *"I have been trained and educated about the AI (relevant to my field)"*. Participant responses to each of these statements were evaluated based on a Likert scale ranging from strongly agree to strongly disagree.

When it comes to the statement of *"All radiology professions curriculum includes at least some basic knowledge of AI"*, overall, the survey results show that the majority of participants agreed or strongly agreed on the significance of including some basic AI knowledge in the radiology curriculum. Regardless of gender, most of the participants (93,78.15%), agreed or strongly agreed with the statement. 30 participants (25.21%) strongly agreed, 63 (52.94%) agreed, 17 (14.28%) were neutral, 7 (5.88%) disagreed, and 2 (1.68%) strongly disagreed. The male participants strongly agreed more frequently than the female participants, with 20 (27.78%) of all male participants strongly agreeing compared to 10 (21.28%) female participants. However, a slightly higher percentage of females agreed with the statement than males, with 25 (53.19%) females agreeing compared to 38 (52.78%) males. Only 7 participants disagreed with the statement out of which the majority were male (5.56% of all males). On the other hand, only

2 participants strongly disagreed with the statement, all of them were females (4.26% of all female participants).

The result of evaluating the participant's perception of whether *"AI should be taught in the undergraduate programme"* shows that overall, most of radiology professionals participated in the survey agreed that AI should be taught in the undergraduate program. However, compared to females, there were more male participants who strongly agreed and who were neutral or disagreed. Out of 119 participants, 66 (55.46%) individuals agreed that AI should be taught in the undergraduate program, 32 (26.89%) strongly agreed, 12 (10.08%) were neutral, and 9 (7.56%) disagreed. Considering the breakdown by gender, 22 (30.56%) males strongly agreed with the statement, while only 10 (21.28%) females strongly agreed. However, the majority of females (42, 89.36%) either agreed or strongly agreed compared to 56 (77.78%) males who agreed or strongly agreed. There were only 9 (7.56%) participants who disagreed with the statement out of which the majority were males (6, 8.33% of all male participants).

A comparable result was observed when participants' perceptions toward the inclusion of AI education in postgraduate programs were evaluated. The survey results show that a vast majority of participants (110, 92.44%) supported the idea of including the AI teaching in postgraduate programs. Out of the 72 male participants, 33 (45.83%) strongly agreed, 34 (47.22%) agreed, 3 (4.17%) were neutral, and only 2 (2.78%) disagreed. Similarly, out of the 47 female participants, 18 (38.30%) strongly agreed, 25 (53.19%) agreed, 2 (4.26%) were neutral, and 2 (4.26%) disagreed. Table 6 and Figure 8 present a detailed summary of the survey findings concerning the participants' perceptions of AI education.

Table 6: Participants' Perceptions of AI Education

Statements	**Female** (n=47)	**Male** (n=72)	**Total** (n=119)
All radiology professions curriculum includes at least some basic knowledge of AI			
Strongly Agree	10 (21.28%)	20 (27.78%)	30 (25.21%)
Agree	25 (53.19%)	38 (52.78%)	63 (52.94%)
Neutral	7 (14.89%)	10 (13.89%)	17 (14.29%)
Disagree	3 (6.38%)	4 (5.56%)	7 (5.88%)
Strongly Disagree	2 (4.26%)	N/A	2 (1.68%)
AI should be taught in the undergraduate programme			
Strongly Agree	10 (21.28%)	22 (30.56%)	32 (26.89%)
Agree	32 (68.09%)	34 (47.22%)	66 (55.46%)
Neutral	2 (4.26%)	10 (13.89%)	12 (10.08%)
Disagree	3 (6.38%)	6 (8.33%)	9 (7.56%)
Strongly Disagree	N/A	N/A	N/A
AI should be taught in the postgraduate programme			
Strongly Agree	18 (38.30%)	33 (45.83%)	51 (42.86%)
Agree	25 (53.19%)	34 (47.22%)	59 (49.58%)
Neutral	2 (4.26%)	3 (4.17%)	5 (4.20%)
Disagree	2 (4.26%)	2 (2.78%)	4 (3.36%)
Strongly Disagree	N/A	N/A	N/A

Note. The % represents the percentage value out of the total number of each category
N/A represents the non-responded option

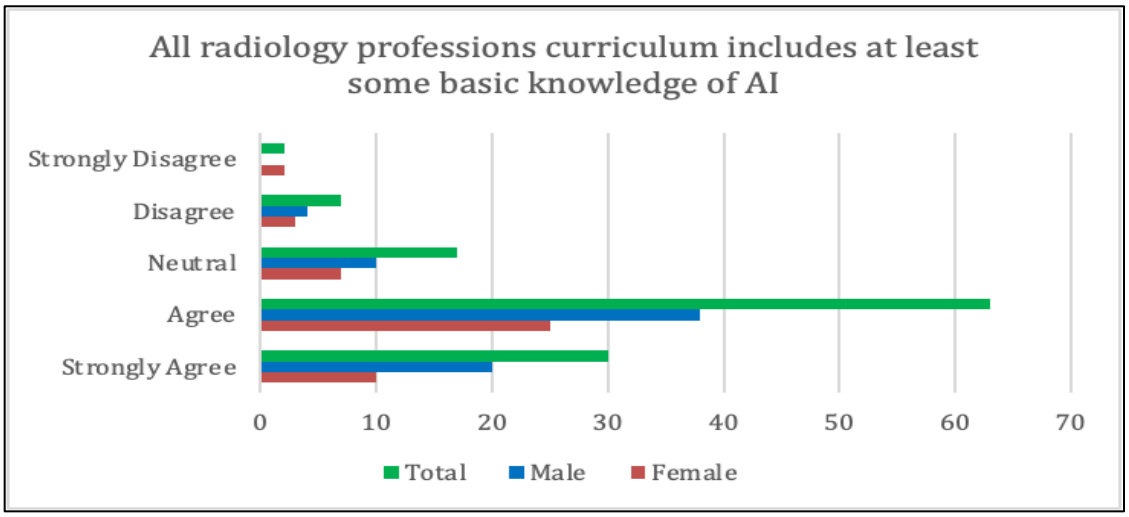

Figure 8: Participants' Perceptions of AI Education in the Radiology Curriculum

When it comes to the participant's current level of AI skills and experience, analysis of the survey findings shows that out of 119 participants, a total of 34 (28.57%) participants agreed or strongly agreed with having all the categories of "having a basic understanding", "working knowledge", and "have received training and education about AI". Only 3 (2.52%) participants, reported having no AI basic knowledge, working knowledge, or having been trained and educated about AI. Notably, among these participants, 2 were female. Regardless of gender, the majority of participants (85, 71.43%) have either agreed or strongly agreed that they have a basic understanding of AI. Specifically, 68 (57.14%) participants agreed, while 17 (14.29%) strongly agreed. 29 (24.37%) participants were neutral, and only 5 (4.20%) participants disagreed or strongly disagreed. It is interesting to note that male participants were more likely than female participants to agree or strongly agree that they have a basic understanding of AI. Specifically, 57 (79.17%) males agreed or strongly agreed, while only 28 (59.57%) females agreed or strongly agreed. On the other hand, only a minority of participants (5, 4.20%) reported not having a basic understanding of AI. Among all, 29 (24.37%) participants were neutral about having a basic understanding of AI with a higher percentage of females than males.

According to the survey results that evaluated the participants' AI experience and skills, regardless of their gender, a considerable percentage of the participants (44, 36.97%) agreed or strongly agreed when asked about their working experience. However, male participants (31, 43.06%) had a larger percentage of agree or strongly agree responses than female participants (13, 27.66%). This pattern was similarly observed among participants who had no prior AI working knowledge. Out of the total 119 participants, 37 (31.09%) disagreed or strongly disagreed with the statements, with 19 (26.39%) male and 18 (38.30%) female participants.

These findings imply that male participants may have more AI experience and skills than their female counterparts. Furthermore, a good proportion of participants (38, 31.93%) were neutral toward the statement, demonstrating a lack of a decisive answer. Overall, it seems that male participants feel more confident about their AI working knowledge than female participants.

The survey results related to whether the participants have been trained and educated on AI show that a good number of the participants (41, 34.45%), regardless of their gender, agreed or strongly agreed that they have received education and training on AI. It seems that the higher percentage of participants who agreed or strongly agreed with the statement were male (28, 38.89% of all male participants) compared to only 13 female participants which count for 27.66% of all female participants. It is worth mentioning that there were more significant numbers of responses (78, 65.55%) in the disagree, strongly disagree, and neutral categories. Considering the gender breakdown, the percentage of female participants (34, 72.34%) who responded as disagree, strongly disagree or neutral was higher than their male counterparts (44, 61.11% of all male participants). Overall, it seems that among all, male participants were more educated or trained in AI applications than female participants. Table 7 provides a detailed overview of the survey data concerning the participants' level of AI knowledge and skills.

3.6.3. Participants' AI Knowledge and Skills Development

To better understand radiology professionals' perception of AI, it is important to evaluate not only their level of knowledge about AI but also to learn about the sources through which they have gained their AI knowledge. This can provide useful insight into the participants' level of enthusiasm to enhance their AI knowledge and skills.

Table 7: Participants' Level of AI Knowledge and Skills

Statements	**Female** (n=47)	**Male** (n=72)	**Total** (n=119)
I have a basic understanding of AI			
Strongly Agree	6 (12.77%)	11 (15.28%)	17 (14.29%)
Agree	22 (46.80%)	46 (63.89%)	68 (57.14%)
Neutral	16 (34.04%)	13 (18.06%)	29 (24.37%)
Disagree	2 (4.26%)	2 (2.78%)	4 (3.36%)
Strongly Disagree	1 (2.13%)	N/A	1 (0.84%)
I have a working knowledge of AI			
Strongly Agree	4 (8.51%)	7 (9.72%)	11 (9.24%)
Agree	9 (19.15%)	24 (33.33%)	33 (27.73%)
Neutral	16 (34.04%)	22 (30.56%)	38 (31.93%)
Disagree	16 (34.04%)	18 (25.00%)	34 (28.57%)
Strongly Disagree	2 (4.26%)	1 (1.39%)	3 (2.52%)
I have been trained and educated about the AI			
Strongly Agree	4 (8.51%)	8 (11.11%)	12 (10.08%)
Agree	9 (19.15%)	20 (27.78%)	29 (24.37%)
Neutral	13 (27.66%)	19 (26.39%)	32 (26.89%)
Disagree	19 (40.43%)	18 (25%)	37 (31.09%)
Strongly Disagree	2 (4.26%)	7 (9.72%)	9 (7.56%)

Note. The % represents the percentage value out of the total number of each category
N/A represents the non-responded option
* AI consider refer to AI relevant to participants' field

In fact, understanding how people acquire their knowledge may help better understand their viewpoints and decision-making behaviours. Therefore, a section of the survey was devoted to evaluating the methods by which participants had acquired their AI knowledge and skills. This assessment was accomplished by presenting respondents with two statements: "My knowledge of AI is" and "My skill in AI is developed through" each with multiple response alternatives. The response options for both statements were "Self-taught", "Attending courses", "Postgraduate training", "Work-related activities", and "No knowledge". The result of the survey shows that regardless of gender, most of the participants acquired their AI knowledge mainly through self-teaching (66, 55.46%). In general, male participants demonstrated a higher inclination for self-

teaching (43, 59.72% of all male participants) compared to their female counterparts (23, 48.94% of all female participants). Following the self-taught method, male participants indicated that they have obtained their AI knowledge through postgraduate training (11, 15.28%), attending courses (8, 11.11%), and work-related activities (5, 6.94%). Additionally, 5 (6.94%) of the male participants admitted to having acquired no knowledge of AI. In contrast, after the self-taught method, female participants primarily relied on attending courses to acquire AI knowledge, with 11 females (23.40%) reporting this method, followed by work-related activities (9, 19.15%). Only 1 female participant (2.13%) claimed to have obtained AI knowledge through postgraduate training. These results show that male participants had a higher level of AI-related academic education in their field of expertise compared to female participants. When it comes to the development of AI skills by the participants in the study, the survey results reveal that 50% of male participants developed their AI skills through self-teaching as demonstrated by 36 out of 72 male respondents. They also obtained AI skills through work-related activities (14,19.44%), attending courses (13,18.06%), and postgraduate training (3,4.17%). Only 6 (8.33%) male participants selected the no-knowledge response. On the other hand, females mainly developed their AI skills through work-related activities and self-teaching as reported by 14 (29.79%) and 13 (27.66%) participants respectively. A good percentage of female participants also report that they gain their AI skills through attending courses (12,25.53%). Additionally, only 2 (4.26%) female participants claimed that they had acquired AI skills through postgraduate training. Overall, the results indicate that male participants relied more on self-teaching methods compared to female participants to develop their AI skills. Figure 9 and Table 8 provide

comprehensive information on the methods used by the participants to develop their AI knowledge and skills.

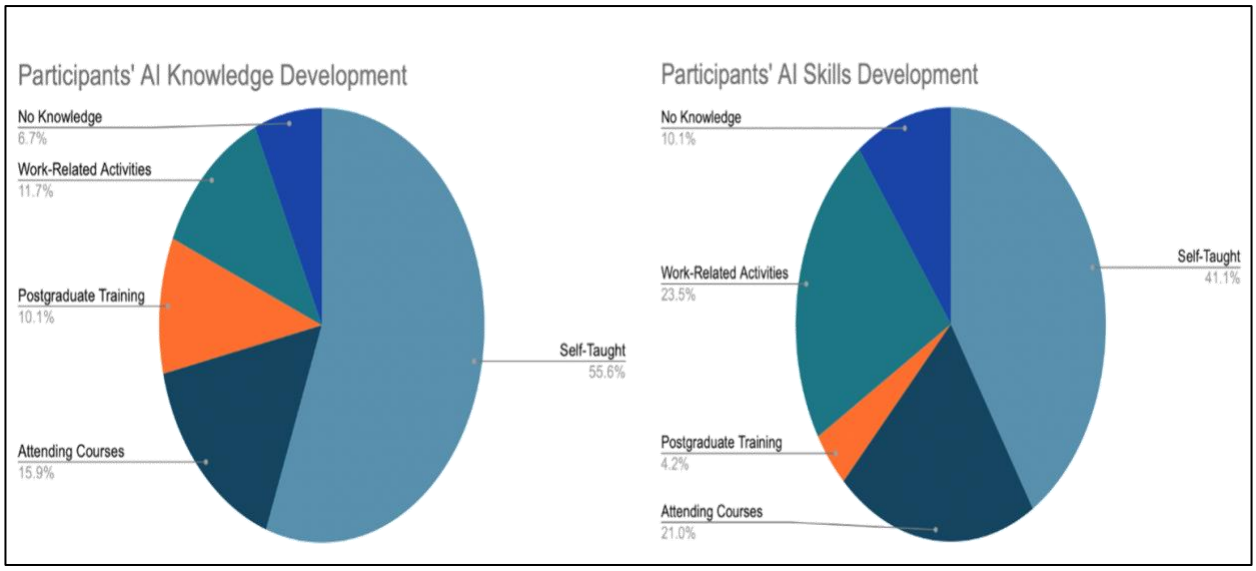

Figure 9: Methods Used to Develop AI Knowledge and Skills

Table 8: Participants Used Methods to Acquire AI Knowledge and Skills

Statements	**Female** (n=47)	**Male** (n=72)	**Total** (n=119)
My knowledge of AI is			
Self-taught	23 (48.94%)	43 (59.72%)	66 (55.46%)
Attending courses	11 (23.40%)	8 (11.11%)	19 (15.97%)
Postgraduate training	1 (2.13%)	11 (15.28%)	12 (10.08%)
Work-related activities	9 (19.15%)	5 (6.94%)	14 (11.76%)
No knowledge	3 (6.38%)	5 (6.94%)	8 (6.72%)
My skill in AI is developed through			
Self-taught	13 (27.66%)	36 (50.00%)	49 (41.18%)
Attending courses	12 (25.53%)	13 (18.06%)	25 (21.00%)
Postgraduate training	2 (4.26%)	3 (4.17%)	5 (4.20%)
Work-related activities	14 (29.79%)	14 (19.44%)	28 (23.53%)
No knowledge	6 (12.77%)	6 (8.33%)	12 (10.08%)

Note. The % represents the percentage value out of the total number of each category
N/A represents the non-responded option

3.7. Participants' AI Readiness Analysis

To evaluate the readiness of participants with implementing AI in radiology practices, the survey included three parts through which it aimed to assess participants' perceptions regarding the readiness of their organizations. This can include their own AI experience as well. The first part included two statements: “At my organization, there is someone responsible for AI” with response options as follows: “Yes”, “No”, or “I'm not sure”. The second statement was “For my work AI is”. This statement was selected in order to evaluate participants' level of experience on a six-point Likert scale, with response options including: “A big part of what we do”, “A small part”, “We’re beginner”, “It is future plan”, “We are not looking at or planning for”, and “I have no idea”. The third statement provided the respondents with the following question: “Does your work organization have a strategy for AI?” this question was selected to assess participants' perceptions of the readiness of their organizations when it comes to AI strategy implementation on a four-point Likert scale, with response options including: “Yes”, “No”, “We're developing one” and “I have no idea”.

The survey results show that out of the 119 respondents, only 23 (19.33%) participants responded with "Yes" claiming that their organization has someone responsible for or in charge of AI. The majority of the participants (49, 41.18%) responded with "No" confirming that their organization has not assigned anyone to be responsible for AI. On the other hand, a considerable percentage of participants (47, 39.50%) responded with "I'm not sure," demonstrating their skepticism or lack of knowledge regarding whether their organization has assigned someone to be responsible for AI or not. When it comes to gender, the survey results show that the majority of both male (56, 77.78%) and female (40, 85.11%) participants responded with "No" or "I'm not

sure". These results may show the lack of participants' understanding regarding the process of AI implementation in their organization which can represent the lack of organizational readiness when it comes to assigning someone to be responsible for AI. Only a small number of male (16, 22.22%) and female (7, 14.89%) participants answered "Yes", claiming that their organization has assigned someone to be responsible for or in charge of AI.

In terms of how long the participants are experienced using AI at their work, the survey results show that irrespective of their gender, a considerable percentage of participants (52, 43.70%) responded as " I have no idea" or "It's a future plan". Furthermore, 31 (26.05%) participants stated that they are beginners or that AI covers a small part of their work. Only 19 (15.97%) participants reported having extensive experience working with AI and that AI covers a significant aspect of their work. The aforementioned survey findings show that participants in general have limited AI working experience. Interestingly, 17 (14.29%) participants reported that they are not currently using or intend to use AI in their organization, emphasizing the limited level of AI utilization or adoption among the participants. Breaking down the responses by gender, the survey results show that male and female participants responded the statement differently and there is no clear pattern in terms of gender variation. The responses of both gender categories indicate that AI is not very important for their work. Out of all participants, 24 (51.06%) females and 28 (38.89%) males responded as "I have no idea" or "it's a future plan", while 10 (21.28%) females and 21 (29.17%) males demonstrate having a low level of AI work experience by selecting "A small Part" or "we are beginners". An almost similar percentage of female and male participants claimed that "AI covers a big part of their work" and that "We are

not looking at or planning for". In general, the responses of male and female participants were similar, and there is no significant difference between the responses of the two groups.

When it comes to participants' perceptions of their organizations' readiness for AI strategy implementation, the results of the survey show that out of 119 respondents, 43 (36.13%) answered as "have no idea", while 32 (26.89%) claimed that their organization has no AI strategy in place, and 12 (10.08%) reported that they are in the process of developing a strategy. Only 32 (26.89%) participants reported that their organizations already have a strategy for AI implementation. Considering the responses by gender, the survey results show that more than half of the female respondents (32, 68.09%) selected either "No" or "I have no idea" regarding whether their organization has any strategy for AI implementation. A similar response pattern was seen among the male respondents, with 43 (59.72%) reporting "No" or "I have no idea". However, there was some difference observed between the two gender categories who reported "Yes" indicating that their organizations already have an AI strategy in place or selected "We are developing one" confirming that their organization is in the process of developing a strategy (29 (40.28%) of male participants vs. to 15 (31.91%) of female participants). Table 9 shows a summary of survey results regarding how the participants perceive their readiness for AI implementation in terms of individual experience or their organizational readiness.

3.8. Participants' Perception of AI Implementation Challenges Analysis

Given the importance of AI implementation challenges, a part of the survey was dedicated to evaluating what challenges participants perceived as the biggest challenges for AI implementation. The answer to this question was structured on a six-point Likert scale, with

Table 9: Participants' AI Readiness

Statements	**Female** (n=47)	**Male** (n=72)	**Total** (n=119)
At my organization there is someone responsible for AI			
Yes	7 (14.89%)	16 (22.22%)	23 (19.33%)
No	20 (42.55%)	29 (40.28%)	49 (41.18%)
I'm not sure	20 (42.55%)	27 (37.5%)	47 (39.50%)
For my work AI is			
A big part of what we do	8 (17.02%)	11 (15.28%)	19 (15.97%)
A small part	2 (4.26%)	13 (18.06%)	15 (12.60%)
We're beginner	8 (17.02%)	8 (11.11%)	16 (13.45%)
It is future plan	10 (21.28%)	18 (25.00%)	28 (23.53%)
We are not looking at or planning for	5 (10.64%)	12 (16.67%)	17 (14.29%)
I have no idea	14 (29.79%)	10 (13.89%)	24 (20.17%)
Does your work organization have a strategy for AI?			
Yes	9 (19.15%)	23 (31.94%)	32 (26.89%)
No	12 (25.53%)	20 (27.78%)	32 (26.89%)
We're developing one	6 (12.77%)	6 (8.33%)	12 (10.08%)
I have no idea	20 (42.55%)	23 (31.94%)	43 (36.13%)

Note. The % represents the percentage value out of the total number of each category
N/A represents the non-responded option

response options including: "Knowledge", "The skills development", "It is hard to find good education and training courses in AI", "It is hard to educate and train the current staff in AI technology", "It is hard to implement AI in the work and practice", and "Graduates aren't leaning AI knowledge and skills at university". In this section of the survey, participants were given the choice of selecting more than one answer.

The results of the survey show that the most selected answer by participants demonstrating their perception of the challenges involved in AI implementation was the lack of "AI knowledge*"* which has been selected by 51 (42.86%) participants out of which the majority

were male (38, 52.78%) and only 13 (27.66%) were female participants. Following the "knowledge", the most selected challenges of AI implementation were skills development and finding good education and training courses in AI which were selected by 48 (40.34%) and 40 (33.61%) respondents respectively. Additionally, 32 (26.89%) respondents selected "Graduates aren't learning the AI knowledge and skills at university" as a key challenge to the implementation of AI. The least selected AI challenges by participants were "It is hard to educate and train the current staff in AI technology" and "It is hard to implement AI in the work and practice" which were selected by 21 (17.65%) and 20 (16.80%) participants, respectively.

When examining the responses considering the gender differences, the finding of the survey shows that male participants mainly selected challenges such as the lack of AI knowledge, lack of AI skills development, and difficulties in having access to good AI education and training courses. On the other hand, female participants mainly selected a lack of AI skills development and difficulties accessing good AI education and training as the key challenges of AI implementation. Table 10 and Figure 10 provide a comprehensive summary of the survey findings related to participants' perceptions of the challenges associated with implementing AI in radiology practices.

3.9. Participants' Perception of AI Application Analysis

To evaluate the perception the participants have toward implementing AI in the radiology setting, it is very important to understand what AI applications participants need the most in their practice. Therefore, the last part of the survey was dedicated to asking the question "Which AI relating application do you most need in your work?".

Table 10: Participants' Perceived Challenges of AI Implementation

Statements	**Female** (n=47)	**Male** (n=72)	**Total** (n=119) *
Knowledge	13 (27.66%)	38 (52.78%)	51 (42.86%)
The skills development	17 (36.17%)	31 (43.06%)	48 (40.34%)
Graduates aren't learning AI knowledge and skills at university	16 (34.04%)	16 (22.22%)	32 (26.89%)
It is hard to educate and train the current staff in AI technology	10 (21.28%)	11 (15.28%)	21 (17.65%)
It is hard to implement AI in the work and practice	9 (19.15%)	11 (15.28%)	20 (16.81%)
It is hard to find good education and training courses in AI	17 (36.17%)	23 (31.94%)	40 (33.61%)

Note. The % represents the percentage value out of the total number of each category
N/A represents the non-responded option
*Participants were allowed to choose more than one statement

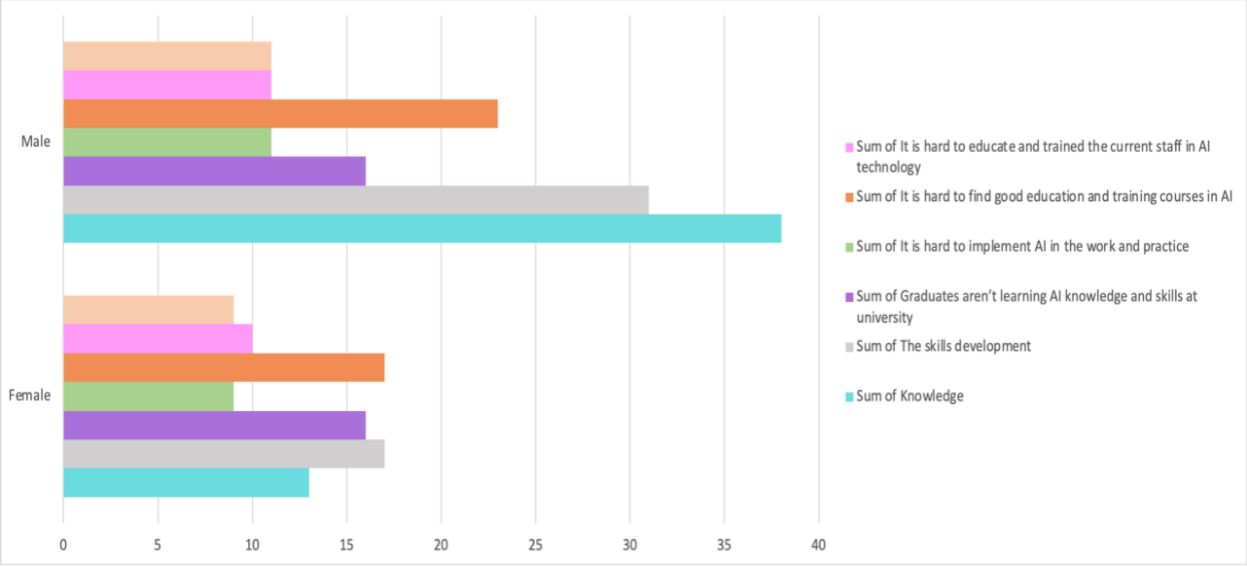

Figure 10: Participants' Perceived Challenges of AI Implementation Versus Gender

The answer to this question was structured on an eight-point Likert scale, with response options including: “Dose management”, “Quality Control”, “Image Evaluation”, “Image Interpretation”,“ Image Post-processing”, “ Communication”, “Teaching & Mentoring”, and “others”. In this section of the survey, participants were given the choice of selecting more than one answer. Regardless of gender, “Dose management” and “Quality control” were the AI applications selected the most by the participants as the most requires AI applications in their practice. These applications were selected by 66 (55.46%) and 63 (52.94%) participants respectively. The least selected answer, on the other hand, was "Other" which was selected by 8 (6.72%) participants who were interested in AI applications that were not listed in the provided choices without providing any suggestions.

When it comes to analysing the survey results considering the gender of the participants, the findings of the survey show that the most frequently selected AI applications by male participants were "Dose management", “Quality control”, and "Image evaluation” which were selected by 39 (54.17%), 39 (54.17%), and 33 (45.83%) respectively. On the other hand, female participants mainly selected AI applications related to "Dose management”, "Quality control”, and” Teaching and mentoring”, these applications were selected by 27 (57.45%), 24 (51.06%), and 18 (38.30%) of female participants respectively.

Table 11 and Figure 11 provide a comprehensive overview of the survey results related to participants’ perceptions of the most required AI applications in their practice.

Table 11: Participants' Perception of The Most Required AI Applications

Statements	**Female** (n=47)	**Male** (n=72)	**Total** (n=119) *
Dose management	27 (57.45%)	39 (54.17%)	66 (55.46%)
Quality control	24 (51.06%)	39 (54.17%)	63 (52.94%)
Image evaluation	13 (27.66%)	33 (45.83%)	46 (38.66%)
Image interpretation	15 (31.91%)	25 (34.72%)	40 (33.61%)
Image post-processing	15 (31.91%)	28 (38.89%)	43 (36.13%)
Communication	9 (19.15%)	16 (22.22%)	25 (21.00%)
Teaching and mentoring	18 (38.30%)	15 (20.83%)	33 (27.73%)
Others	3 (6.38%)	5 (6.94%)	8 (6.72%)

Note. The % represents the percentage value out of the total number of each category.
N/A represents the non-responded option.
*Participants were allowed to choose more than one statement

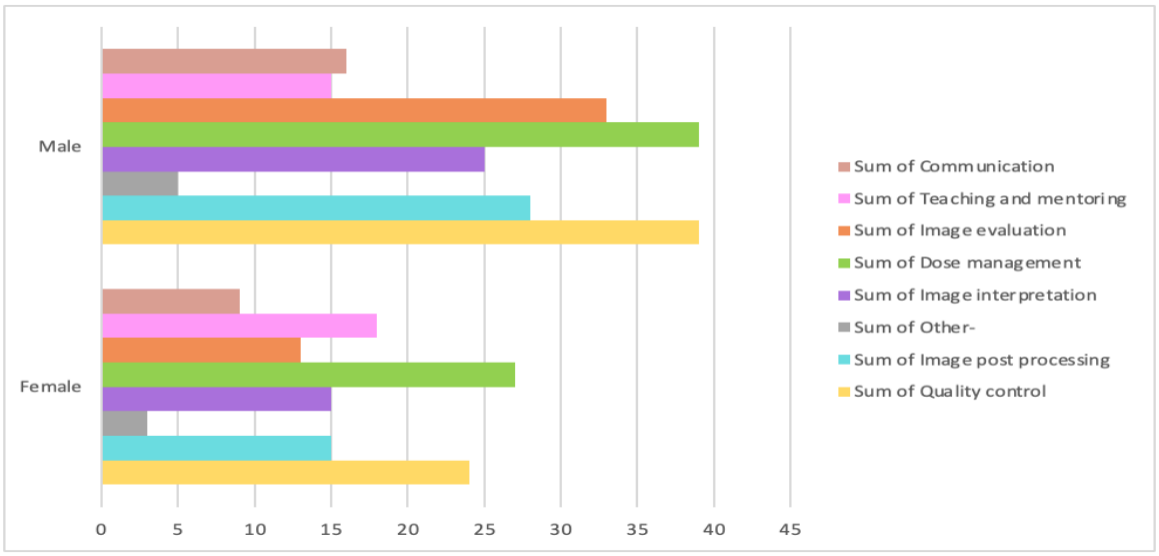

Figure 11: Participants' Perception of The Most Required AI Applications Versus Gender

3.10. Additional Insight

Through analyzing the survey data, it has been noticed that although, the majority of participants (88.24%) agreed that AI plays an important role in radiology practices, however, when participants were asked how well they understand AI, 46 (38.66%) participants confirmed either they have no idea about AI or having a limited AI understanding. On the other hand, the assessment of participants' level of AI knowledge reveals that 85 (71.43%) participants have only a basic understanding of AI. These results confirm that a considerable number of participants had a low understanding of AI, and their perception of AI usefulness may not be based on the true understanding of AI. Therefore, participants' level of AI perceived usefulness may not be as accurate as it has been reported.

4. Theoretical Framework

While IT utilization studies including the use of AI are common in the Management Information Systems (MIS) literature, their application in the healthcare field is generally rare, and previous research often lacked a well-established theoretical basis. As argued by Dishaw and Strong (1999), during the past decade, two important models examining IT utilization behaviour have been identified in the MIS literature. These models are the Task-Technology Fit Model (TTF) and the Technology Acceptance Model (TAM). Both models serve as essential theoretical frameworks for examining the factors that influence software utilization and its connection to user performance. Although both models provide unique insights into utilization behaviour, they share some characteristics in common. TAM emphasizes the fact that the attitudes that users develop toward the utilization of a specific IT are based on their perceived usefulness and ease of

use. On the other hand, TTF focuses on how well the provided IT functionality aligns with the user's task needs. While each of the models is informative and has strong explanatory power, integrating constructs from both models could lead to a significant improvement in the explanatory power of the integrated model than either model alone (Dishaw & Strong, 1999).

In the research study conducted by Dishaw and Strong (1999) who developed the integrated model of TAM/TTF, the results confirm that adding the constructs of TTF to the TAM model results in an explaining a higher-level variance in IT utilization than when TAM or TTF used separately. Studies that focused on the use of e-commerce applications and online courses have confirmed the TAM/TTF high predictability. Specifically, TAM/TTF model was able to explain 76% of the variance in the intention to adopt e-commerce (Shih & Chen, 2013) and 95.7% of the variance in the intention to continue utilizing online courses (Wu & Chen, 2017).

According to Marikyan and Papagiannidis (2022b), the validity of TAM/TTF was tested in variety of geographical locations and cultural contexts, showing some evidence of the model's validity. For example, in China, Yuan et al. (2016) used TAM/TTF integrated model to evaluate the intention to continue using mobile banking and were able to explain 53% of the variance in the outcome variable. In particular, the intention to continue using was positively influenced by task-technology fit and perceived usefulness. Likewise, in Jordanian enterprises, TAM/TTF integrated model was found to be a valid model for assessing visual analytics adoption. In the study conducted by Daradkeh (2019), the TAM/TTF integrated model was able to account for approximately 60% of the variance in behavioural intention.

As argued by Dishaw and Strong (1999), it is evident that the TAM/TTF integrated model has demonstrated a greater capacity to explain more of the variance in the dependent

variable, technology utilization, compared to either the TAM or TTF models used independently. The increase in the amount of variance explained is significant at the 0.05 level for both cases. According to Dishaw and Strong (1999), adding TTF constructs to TAM results in a noteworthy improvement (with a change from 36% to 51%, significant at 0.025), and adding TAM to TTF also leads to a significant improvement (with a change from 41% to 51%, significant at 0.04) explaining more of the variance in the technology utilization.

As argued by Dishaw and Strong (1999), The TAM's two main independent variables, "perceived usefulness" and "perceived ease of use", still play an important role in the integrated model of TAM/TTF in terms of explaining the utilization with a total effect of 0.37 and 0.26 respectively rather than 0.52 and 0.44 in TAM. On the other hand, the strongest contributor to explaining utilization in the TAM/TTF integrated model is "task characteristics", with a total effect of -0.61. Also, "task-technology fit" has a stronger effect of 0.29 compared to "perceived ease of use", which has an effect of 0.26. As the result of model integration, the TAM/TTF integrated model explains more variance of technology utilization (51% compared to 36% in TAM). This variance is explained by "perceived usefulness"; "perceived ease of use"; "task-technology fit"; "task characteristics"; and "tool experience", rather than just "perceived usefulness" and "perceived ease of use" as in TAM. When it comes to "intention to use" and "attitude", the total effect of both is similar in TAM and TAM/TTF integrated models (Dishaw & Strong, 1999).

By taking into account the aforementioned evidence on the reliability of the TAM/TTF integrated model, this thesis aims to partially adopt the integrated model of TAM/TTF proposed by Dishaw and Strong (1999). Specifically, the study aims to investigate whether this integrated

model can be utilized to demonstrate the radiology professionals' perception of AI usefulness in radiology practices. The study seeks to contribute to the existing literature on technology perception in the healthcare sector and specifically in radiology practices by exploring the relationship between the integrated model of TAM/TTF and radiology professionals' perceptions of AI usefulness in radiology settings. The following section is dedicated to explaining each construct of the adopted TAM/TTF integrated model that is presented in Figure 12 (adapted from Marikyan & Papagiannidis, 2022b).

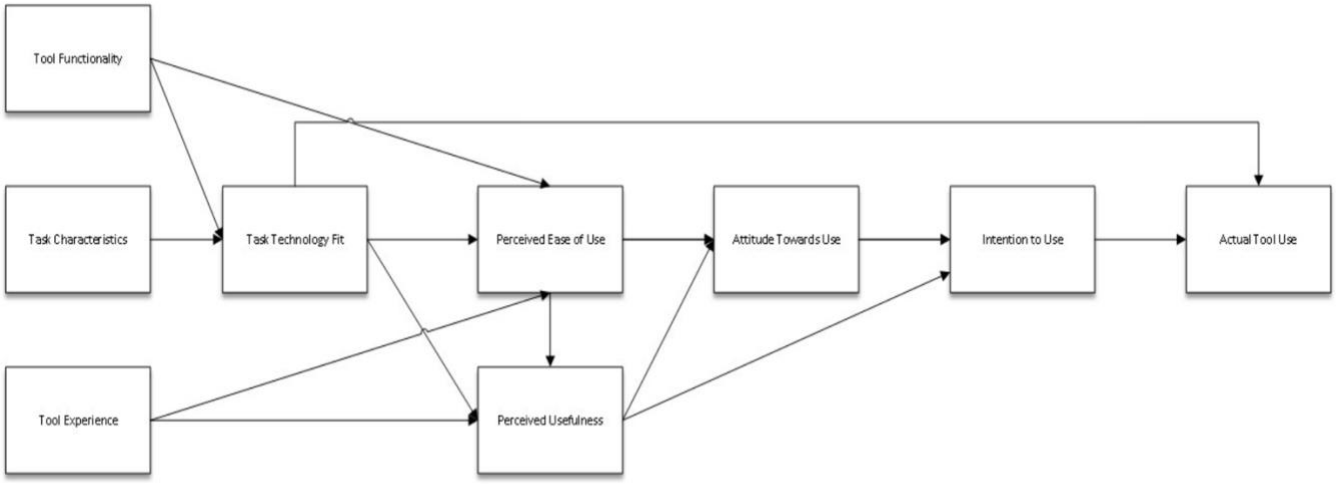

Figure 12: Integrated model of TAM/TTF proposed by Dishaw and Strong (1999)
Note: Figure is adopted from "Task-Technology Fit: A review" Marikyan, D. & Papagiannidis, S. (2022b).

4.1. TAM/TTF Integrated Model Variables Identification

The TAM has been examined in various IT usage research studies (Adams et al., 1992; Davis et al.,1989; Mathieson, 1991, Straub et al., 1997). In Devis (1989) study, the TAM makes

the essential assumption that the behaviour is voluntary or at the user's discretion. Two key independent variables, namely, “perceived ease of use”, and “perceived usefulness” has been identified in TAM model where “perceived ease of use” influence “perceived usefulness”. As argued by Dishaw and Strong (1999), TAM considers “perceived ease of use”, and “perceived usefulness” as two external variables by which “attitude”, “intention to use” and eventually the “actual use” can be determined. Therefore, TAM does not require customization for each specific behaviour, as long as it is related to IT use.

According to Davis (1989), “perceived usefulness” is defined as *“the individual's perception of the extent to which the use of a given technology improves performance”* (Marikyan & Papagiannidis, 2022, p.2), and “perceived ease of use” is defined as *“the degree to which a person believes that using a particular system is free of effort”* (Marikyan & Papagiannidis, 2022, p.2). According to Dishaw and Strong (1999), considering the fact that users utilize IT solutions in order to accomplish the organizational task, one of the drawbacks or limitations of the TAM framework in comprehending IT usage is its lack of focus on tasks. This limitation of TAM can be addressed by TTF framework.

According to Goodhue & Thompson (1995), TTF model consists of five constructs, namely, “technology characteristics or tools functionality”; “task characteristics”; “task-technology fit”; “technology utilization”; and “performance impact”. In TTF, while the dimensions of technology and its utilization are determined by “technology characteristics” and “task characteristics”, the “task-technology fit” factor represents how individuals perceive the fit between task and technology (task-technology fit). As argued by Marikyan and Papagiannidis (2022b), “technology characteristics” or “tool functionality” refer to *“functions or attributes that*

are particular to a specific technology". "Task characteristics" on the other hand, can be measured by factors which impact how heavily users rely on particular aspects of IT solutions, these factors include task interdependence, non-routineness, and job title (Marikyan & Papagiannidis ,2022b).

According to Goodhue & Thompson (1995), there are three propositions for TTF model. As per the first proposition, both "technology characteristics" and "task characteristics" contribute to determining how users evaluate the "task-technology fit". In fact, the extent to which a system helps individuals in accomplishing their required tasks can be measured through users' assessment of eight dimensions, including, locatability, compatibility, production timeliness, quality, authorization, training and /or ease of use, reliability of the systems, and relationship with the user. The theory's second proposition state that the individuals' utilization of information systems depends on how well they do perceive the fit (how well the technology can fit their needs). The third proposition of the theory state that the positive assessment of how well the technology fits the task (task-technology fit) not only anticipates the technology utilization but positively impacts a user's perceived performance in completing a task.

According to Bandura (1982), perceived performance can be defined as *"the level to which individuals perceive that performance can be improved with the help of technology".* In the integrated model of TAM/TTF, the variables' relationships in the TAM and TTF models remained the same (Marikyan & Papagiannidis ,2022b).

As originally proposed by Davis (1989), in the integrated model as well, TAM represents how "perceived usefulness "and "perceived ease of use" interact to influence attitude, intention, and usage behaviour and TTF is considered a model that examines the "actual tool use" as

impacted by “tool experience” and “technology-task fit”, where the “technology-task fit”, in turn, is influenced by “tool functionality” and “task requirements” (Marikyan & Papagiannidis, 2022b). According to Dishaw and Strong (1999), the “perceived usefulness” and “perceived ease of use” will be increased if users believe that the technology is a good fit for the required task to be accomplished. On the other hand, as per Dishaw and Strong (1999) study, there is a positive relationship between “technology functionality” and “task-technology fit”. This relationship has been also supported by other earlier studies (Goodhue,1995; Goodhue & Thompson,1995), where the results of these studies show that “task-technology fit” can be increased as a result of the increase in information technology functionality. Additionally, as shown in Figure 14, in the integrated TAM/TTF model, there is a correlation between each of “technology functionality” and “Tool or technology experience” with the” perceived ease of use”. This can be interpreted in the way that technologies with a higher range of functionality are more likely perceived to be more challenging to use or operate (Dishaw & Strong,1999).Therefore, those users with a higher level of experience using a particular technology, are more likely to perceive the technology as being easy to use. Additionally, “tool experience” has a direct effect on “perceived usefulness” where the higher level of technology ease of use can be perceived by individuals who are more experienced in using that particular technology (Dishaw & Strong,1999).

Although in the TTF model, there is a direct correlation between “tool experience” and “Actual tool use”, however in the integrated TAM/TTF model, this relation exists through “perceived ease of use” (Dishaw & Strong,1999). On the other hand, “task-technology fit” also has a direct effect on “perceived ease of use”, this can be explained in the way that the higher the fit between the task and technology perceived by users, it will be more likely that users perceive

that specific technology as easier to be used (Dishaw & Strong,1999).

The TAM/TTF integrated model's strong predictive power made it a reliable model to be adopted in many research studies in different fields. However, unlike TAM, the application of TAM/TTF integrated model in the healthcare industry is still limited.

5. Statistical Analysis

In this quantitative research study, to examine the relationship between a number of independent variables and a dependent variable, the survey data was analyzed using multi-linear regression analysis and the IBM SPSS statistical software version 25.0 was utilized to run the analysis. The P-value threshold of less than 0.05 was used to determine statistical significance and R-squared and adjusted R-squared values were utilized to evaluate the goodness-of-fit of the suggested model. To explain the relationship between the variables, the study used correlation and regression techniques. In order to measure the strength and the direction of the linear relationship between variables, in the study's initial stage, the Pearson Correlation Coefficient was utilized as well.

5.1. Variable Description

In this thesis, the researcher is intended to evaluate the effect of a number of independent variables on a single dependent variable of "AI perceive usefulness" which reflects *"the perception the participants had toward whether AI plays an important role in the practice of radiology professions"*. While analyzing the survey results, only those variables were taken into account which evaluating their effect could help in understanding the perceptions and challenges

related to AI implementation in radiology practices. Therefore, among all the independent variables, the researcher has only evaluated the effect of those variables that were relevant to the thesis topic and research questions. Part of the data analysis section was dedicated to evaluating demographic variables which can provide insights into how different groups of radiology professionals perceive the usefulness of AI technology. These variables included participants' gender, age, education (highest qualification attained), and years of experience in medical imaging. The following section is devoted to describing different categories of variables considered in this study.

5.1.1. AI-Related Variables

The AI-related variables, such as AI functionality, career threat, radiology practice threat, inclusive of AI in radiology education, AI experience and training, AI skills and knowledge development, AI general understanding and familiarity, and general feeling toward AI were most likely utilized to measure the level of AI familiarity and understanding among radiology professionals' participants. For this study "AI Functionality" represents whether "*AI will take place in many applications and/or image production"*. "AI Radiology Threat" and "AI Career Threat", on the other hand, refer to whether "*AI will threaten and/or disrupt the radiology practice"* and *"AI will threaten and/or disrupt some radiology professionals' career"* respectively. In this study, "AI Education" refers to whether *"The Radiology curriculum should include at least some basic knowledge of AI (from radiology professionals' perspective)"*. It is worth noting that for this study "AI Education" is considered any university education regardless of whether it is undergraduate or graduate level of study.

To precisely evaluate how radiology professionals perceive AI usefulness, it is very

important to evaluate the effect of *"participants' basic understanding of AI and whether they are aware of the potential benefits and limitations of AI in radiology*". Therefore, this thesis examined the impact of the "AI basic Understanding" variable in parallel with other variables. Like "AI Basic Understanding", "AI Working Knowledge" which reflects whether *"the participants had a working knowledge of AI"* is a very important variable to be considered since "AI Working Knowledge" can reveal how familiar and comfortable the radiology professionals are with the practical aspects of AI implementation.

The variable "AI Training", on the other hand, represents whether participants *"have been trained and educated about the AI".* "AI Training" is an important variable to be considered besides other variables while evaluating radiology professional's perception of AI usefulness since those radiology professionals who have been trained and educated on AI normally have more reliable knowledge about the potential advantages and limitations that AI applications may provide to the field of radiology in general. In fact, having reliable knowledge of AI applications in radiology practice can impact the way radiology professionals may perceive AI usefulness and their willingness to utilize AI in their practice.

"AI Knowledge Development" and "AI Skill Development" are variables which represent *"how the knowledge and skills of participants have been developed"*.

To evaluate the perception radiology professional may have toward the AI's usefulness in radiology it highly makes sense to consider variables related to how participants developed their AI knowledge and skills. The rationale behind this is that normally those radiology professionals who developed their knowledge and skills via valid resources such as university training courses or work-related activities have a more reliable understanding of AI implementation in

comparison to those who relied on self-taught to develop their AI knowledge and skills. Therefore, both variables, “AI Knowledge Development” and “AI Skill Development” are considered by the researcher to take part while evaluating the perception of AI usefulness among radiology professionals.

“AI Experience” is another very important variable considered by the researcher of this study. “AI Experience” refers to *“The extent to which the participants are engaged in using AI applications”*. This represents whether *“AI is the big part of what they do in practice”* or *“they are beginners when it comes to using AI applications at their work”.*

Besides other considered variables, “AI Feeling” is one of the primary independent variables that has been considered by the researcher for this thesis. “AI Feeling” represents *“the feeling participants have about AI”*. The overall feeling reported by survey participants toward the use of AI in radiology practices ranged from feelings such as *“Excitement”* to *“Overwhelmed”*. These types of feelings according to the literature can influence the way individuals perceive the technology’s ease of use and therefore can impact the perceived usefulness of the technology. According to Venkatesh (2000), as proposed by the TAM3 model, individuals’ perception of a technology's ease of use is influenced by numerous factors, including computer self-efficacy, computer anxiety, computer playfulness, and perceptions of external control. Based on the provided evidence, the researcher included "AI Feeling" as an independent variable in the analysis, taking it into account as one of the anchors proposed by the TAM3 model (Venkatesh & Bala, 2008).

Besides the mentioned variables, the researcher of this study considered "AI Familiarity" as the independent variable for further analysis. "AI Familiarity" represents *“How well*

participants comprehend what is meant by AI and how comfortable they are using AI applications". Many research studies including the research conducted by Sun and Medaglia (2019), have recognized a lack of familiarity and sufficient knowledge as a potential barrier to AI adoption. Therefore, "AI Familiarity" was considered for further analysis.

5.1.2. Organizational-Related Variables

Variables like "AI Organizational In-charge" and "AI Organizational Strategy" represent organizational readiness for AI implementation and adoption. These variables can show whether *"the organization has assigned someone to be in charge of the process of AI implementation and operations"* and *"if the organization has implemented any strategy regarding the use of AI"*. These organizational-related variables can provide useful information about how the management of the organizations to which participants belong perceives AI applications in radiology settings. The AI perceptions of the organization's management, in turn, can influence how radiology professionals perceived AI usefulness. In fact, according to Weiner et al. (2008), organizational readiness can be defined as *"a set of essential factors including, motivational readiness such as the need for change; staff attributes like adaptability; institutional resources like infrastructures; and the organizational climate such as goal clarity"*. Also, according to research studies, in healthcare settings, the existence of organizational readiness enabled healthcare establishments to better accept and implement changes, whereas the lack of organizational readiness increased the risk of technology being rejected by healthcare professionals (Al-Abri, 2007; Jennett et al., 2003). Based on the aforementioned evidence, the researcher has decided to include all variables relevant to organizational readiness for further

analysis.

5.1.3. AI-Challenge Variables

Variables highlighted by participants in the survey as the *"biggest challenges for AI implementation in their work"* are highly significant to be considered in this study as such variables can impact the radiology professionals' perception of AI usefulness and eventually can help in identifying potential obstacles to the AI implementation and adoption in radiology. These include variables such as *"lack of AI knowledge"; "lack of skills using AI"; "lack of AI education"; "challenges involved with implementing AI in the work and practice";* and *"lack of proper AI training among radiology professionals".*

5.1.4. AI Application-Specific Variables

The application-specific variables represent those applications highlighted by participants as the most required AI relating applications in their practices. These include variables such as *"image interpretation", "dose management", "teaching and mentoring", image evaluation", "communication",* and *"quality control".* For this study, the researcher considered only those applications reported the most by the participants of the survey as well as in the available related research studies. The "AI Application-Specific" variables are very important as they may provide valuable insights into the true needs of radiology professionals and how AI applications can be used to fulfill those needs, allowing the best Task-Technology fit to be acquired.

In order to acquire a deeper understanding of the survey data, a descriptive analysis has been performed. Table 12 presents the descriptive statistics of variables that were eligible to be included in this study considering the adopted integrated model of TAM/TTF.

Table 12: Variables' Descriptive Statistics

Variables	N	Mean	SD	Min	Max	p1	p99	Skew.	Kurt.
AI Perceive Usefulness	119	4.328	.793	1	5	1	5	-1.47	6.368
AI Future Impact	119	4.403	0.642	2	5	2	5	-0.986	4.57
AI Working Knowledge	119	3.126	1.013	1	5	1	5	0.139	2.198
AI Feeling	119	4.765	1.212	2	6	2	6	-0.917	2.997
AI Experience	119	2.672	1.59	1	5	1	5	0.28	1.497
AI Challenge-Implementation	119	0.168	0.376	0	1	0	1	1.775	4.152
AI App-Quality Control	119	2.529	0.501	2	3	2	3	-0.118	1.014

Note: p1 and p99 represent the 1st percentile(lower) and 99th percentile(upper) respectively
"Skew." represent Skewness; "Kurt." Represent Kurtosis

5.2. Data Analysis

To determine which of the eligible independent variables (listed in Table 12) are significantly correlated with participants' perceived usefulness of AI, a multiple regression analysis has been conducted. To prevent any situation that could lead to unreliable coefficient estimates and decreased model performance, the multicollinearity has been checked using the Variance Inflation Factor (VIF) for each predictor variable. Table 13 shows the results of a multiple linear regression analysis in which all eligible independent variables were included in the model in order to predict the outcome variable. As shown in Table 13, all variables have low VIF values indicating no multicollinearity issues in our model.

In order to determine if the assumption of residual normality is met, this study also conducted a standardized residual analysis. The regression standardized residual histogram, illustrated in Figure 13, indicate that the residuals follow a normal distribution with a standard deviation of 0.974 and a mean of -1.44E-16. As expected in a well-fitted model, this shows that most of the residuals are centered close to zero. According to the histogram, the distribution of

the residuals is approximately normal which means that the assumptions of the linear regression model are met and that the model is a good fit for the dataset. Therefore, given the results of standardized residual analysis, there is enough evidence that the linear regression model is valid and can be used to make accurate predictions. To ensure that the normality assumptions were met, a normal probability plot (normal P-P plot) was also performed as shown in Figure 14. The plot shows that the dataset is approximately normally distributed.

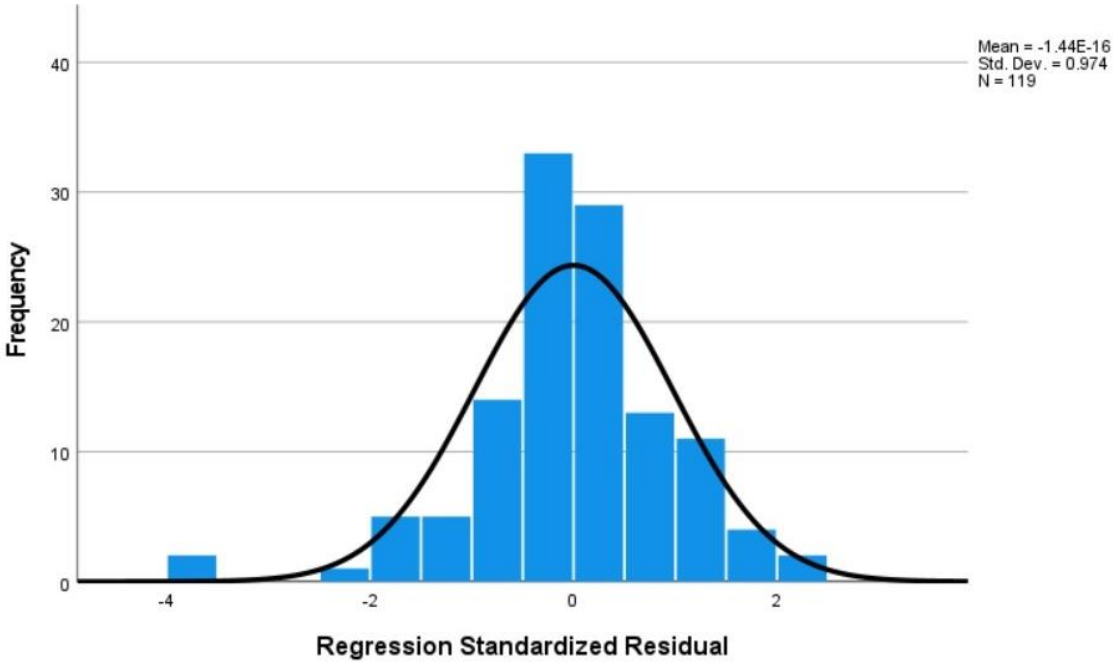

Figure 13: Histogram of Regression Standardized Residual
Note: Dependent Variable is "AI Perceive Usefulness."

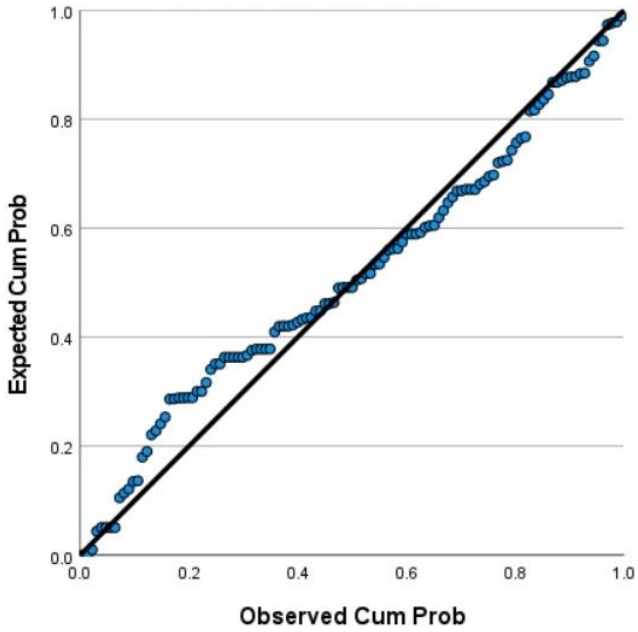

Figure 14: Normal P-P Plot of Regression Standardized Residual

For the categorical variables, the researcher of this thesis had a choice of deploying ANOVA or logistic regression. The former was selected as the primary method. One of the concerns of choosing a linear regression, as argued by Long (1997), is that the linear probability model may violate the homoskedasticity and normality of errors assumptions resulting in invalid standard errors and hypothesis tests. As shown in Figures 13 and 14, the regression standardized residual shows that the linear regression model is valid for the dataset used in this study. Furthermore, as Fox (1997) mentioned, ANOVA can be used with categorical variables, particularly when there is a categorical independent variable (with two or more categories) and a normally distributed interval dependent variable. Finally, the researcher intended to test for differences in the means of the dependent variable broken down by the levels of the independent variable.

For further analysis, SPSS version 25 was used to deploy ANOVA regression on variables. Table 13 shows the regression results with the dependent variable "AI Perceive Usefulness". As shown, all independent variables, except for "AI Working Knowledge," have a significant impact on the dependent variable with p-values of less than the critical value of 0.05. The insignificant value of "AI Working Knowledge" will be discussed later in this section.

Tables 13,14 and 15 show a summary of regression results. For example, as shown in Table 14, the R-squared shows a value of 0.491, indicating it represents almost 50% of the variance for the dependent variable (e.g., "AI Perceive Usefulness") explained by the independent variables in the regression model.

Table 13: Regression Results

	Unstandardized Coefficients		**Standardized Coefficients**			**Collinearity Statistics**	
Model	**B**	**St. Error**	**Beta**	**t**	**Sig.**	**Tolerance**	**VIF**
(Constant)	**0.793**	**0.394**		**2.013**	**0.047**		
AI Future Impact	0.671	0.088	0.543	7.613	<0.001	0.893	1.119
AI Feeling	0.124	0.046	0.190	2.702	0.008	0.922	1.084
AI Working Knowledge	0.104	0.056	0.133	1.868	0.064	0.896	1.116
AI Experience	- 0.105	0.035	- 0.210	-3.035	0.003	0.947	1.056
AI Challenge-Implementation	- 0.375	0.145	- 0.178	-2.589	0.011	0.966	1.035
AI App-Quality Control	0.248	0.108	0.157	2.294	0.024	0.976	1.025

Note: Dependent Variable is "AI Perceive Usefulness"

Table 14: Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.701	0.491	0.464	0.581

Note: Predictors are: (Constant), AI Future Impact, AI Feeling, AI Working Knowledge, AI Experience, AI Challenge-Implementation, AI Application-Quality Control

Table 15: ANOVA Model Summary

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	36.428	6	6.071	17.994	<0.001
Residual	37.790	112	0.337		
Total	74.218	118			

Note: Dependent Variable is "AI Perceive Usefulness"
Predictors are: (Constant), AI Future Impact, AI Feeling, AI Working Knowledge, AI Experience, AI Challenge-Implementation, AI Application-Quality Control

5.3. Summary of Regression Results

In summary, as shown in Table 13, among all the independent variables, "AI Future Impact" is highly significant (<0.001) and has the largest coefficient (0.671), indicating that it has the strongest relationship with the dependent variable (AI Perceive Usefulness). The results also show that among all the variables "AI Experience" and "AI Challenge-Implementation" have negative coefficients (- 0.105 and - 0.375 respectively) and are also statistically significant (p=0.003 and p= 0.011 respectively), indicating that these two variables have an inverse relationship with the dependent variable of "AI Perceive Usefulness". When it comes to "AI Feeling" and "AI App-Quality Control", these variables are both statistically significant (p=0.008 and p= 0.024 respectively) and both have a positive coefficient of 0.124 and 0.248

respectively. The results suggest that both “AI Feeling” and “AI App-Quality Control” variables have a positive relationship with the dependent variable of “AI Perceive Usefulness”. An unexpected finding was that although there is a positive relationship between “AI Working Knowledge” and “AI Perceive Usefulness”, the relationship is not significant ($p=0.064$). In fact, p-value suggests that there is no strong enough evidence supporting a true relationship between the two variables “AI Working Knowledge” and “AI Perceive Usefulness”. Also, according to the ANOVA model summary represented in Table 15, given the degrees of freedom (6) and the significance level ($p<0.001$), the F-statistic value (17.994) suggests that the predictor variables are significantly related to radiology professionals’ AI perceived usefulness.

To measure the strength and the direction of the association between variables, the Pearson Correlation Coefficient has also been conducted. According to the correlations of the variables utilized in the analysis shown in Table 16, all correlations were within the acceptable ranges of -1 and 1 with -1 representing a perfect negative correlation and 1 representing a perfect positive correlation. Among all considered independent variables, the strongest positive correlation (0.587) occurs between “AI Future Impact” and the dependent variable of “AI Perceive Usefulness”. This could imply that individuals who believe that AI will take place in many applications and image production are more likely to perceive AI as a useful solution in radiology practices. On the other hand, the weakest correlation coefficient (-0.002) occurs between "AI Challenge-Implementation" and "AI Future Impact", this indicates that there is a very weak negative linear relationship between these two variables. In fact, there is no meaningful relationship exists between "AI Challenge-Implementation" and "AI Future Impact".

Table 16: Correlation Matrix

		1	2	3	4	5	6	7
1.	**AI Perceive Usefulness**	1.000						
2.	**AI Future Impact**	0.587	1.000					
3.	**AI Feeling**	0.301	0.145	1.000				
4.	**AI Working Knowledge**	0.317	0.286	0.183	1.000			
5.	**AI Experience**	- 0.055	0.156	0.140	0.094	1.000		
6.	**AI Challenge-Implementation**	- 0.187	- 0.002	- 0.154	- 0.034	- 0.077	1.000	
7.	**AI App-Quality Control**	0.178	0.068	0.067	0.051	0.113	0.064	1.000

Note: Dependent Variable is "AI Perceive Usefulness"

5.4. Variable - Theory Mapping

Based on the result of the statistical analysis and specifically the Variance Inflation Factor (VIF) analysis of the survey results, the researcher of this study decided to only consider those independent variables which have a VIF of one or close to one, to explain whether AI plays an important role in radiology practices from the radiology professionals' perspective. In order to evaluate the dependent variable of "AI Perceived Usefulness", the effect of six independent variables was examined in the current research studies, these variables are as follows: "AI Future Impact", "AI Working Knowledge", "AI Experience", "AI Feelings", "AI Challenge-Implementation", and "AI App-Quality Control".

"AI Future Impact" represents the AI applications in the radiology setting and whether the AI will take place in many applications and image production in the radiology department. For this research study "AI Future Impact" is considered as "Tool Functionality" in the TAM/TTF integrated model. Since implementation is a crucial part of the functionality of any technology, the independent variable of "AI Challenge-Implementation" is also considered as part of "Tool Functionality" in the TAM/TTF integrated model.

"AI Working Knowledge" represents the survey participants' perception of having AI working knowledge and skills. According to Venkatesh and Bala (2008) and as suggested in many research studies (Davis et al.,1989; Venkatesh,2000; Davis & Venkatesh,2004), "perceived ease of use" is strongly connected with users' self-efficacy belief and practical knowledge that can be acquired only through experience and skill execution. Also as argued by Rouidi et al. (2022), when it comes to self-efficacy, according to research studies, health professionals may have a high degree of intention to utilize a technology if they have a favourable perception of their technology-related skills. Rouidi et al. (2022) also argued that the result of research studies showed that when the users' IT knowledge is high, they perceive less effort to use that particular technology and therefore, the "perceive ease of use" will be high. Considering the evidence highlighted by the number of studies, in this study "AI Working Knowledge" is considered as a construct that predicts "perceive ease of use". This is very similar to the relationship that exists between "Tool experience" and "perceive ease of use" in TAM/TTF integrated model.

"AI Experience" is another independent variable that was found through this study to have a direct effect on "AI Perceived Usefulness". In this study "AI Experience" represents the level of expertise the participants have using AI applications. "AI Experience" is considered as

"tool experience" in TAM/TTF integrated model. According to the explained literature, individuals who have more experience utilizing AI applications tend to perceive them as easier to be used. Also, the higher level of individuals' experience can lead to a higher level of AI perceived usefulness (Dishaw & Strong,1999).

"AI App-Quality Control" is the other independent variable that was found to be significant in determining "AI Perceived Usefulness". This variable reflects the "clinical task characteristics" participants need to be addressed through the use of AI applications in radiology departments. Therefore, in this study "AI App-Quality Control" is considered as "Task Characteristics" in TAM/TTF integrated model.

"AI Feelings" is the independent variable that represents the feelings participants may acquire by evaluating the technology utilization to fulfill the task they need to accomplish. Considering that according to Goodhue and Thompson (1995) and Goodhue (1992) "task-technology fit" reflects the perception of users toward task-technology fit, in this study "AI Feelings" is considered as the "task-technology fit" construct in the integrated TAM/TTF model. As explained earlier, according to the third proposition of the TAM/TTF model, positive evaluation of the fit between the technology and task in addition to predicting technology utilization can positively influence the perceived performance or the accomplishment of the task by the individual (Goodhue & Thompson, 1995; Goodhue, 1992). Figure 15 shows the TAM/TTF integrated model proposed by this study to examine the AI perceived usefulness by radiology professionals.

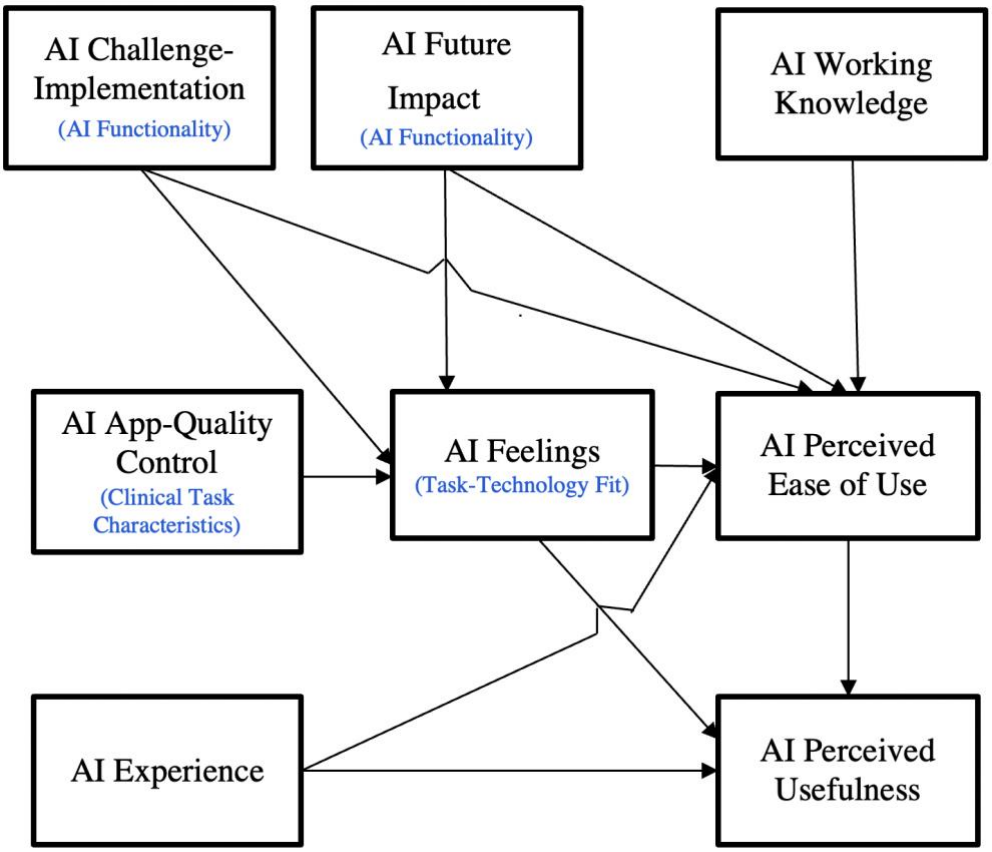

Figure 15: The TAM/TTF Model Proposed for AI Perceived Usefulness in Radiology
Note: The blue highlighted parts represent the construct of the TAM/TTF integrated model to which each independent variable belongs.

6. Discussion

To the best of the researcher's knowledge, this research study accounts for the first of its kind that evaluates the perception radiology professionals may have toward the usefulness of AI applications in radiology settings using the TAM/TTF integrated model proposed by Dishaw and Strong (1999). As mentioned earlier, adding TTF constructs to TAM results in a noteworthy improvement (with a change from 36% to 51%, significant at 0.025), and adding TAM to TTF

also leads to a significant improvement (with a change from 41% to 51%, significant at 0.04) explaining more of the variances in the technology utilization (Dishaw & Strong, 1999). Therefore, adopting a model such as the TAM/TTF integrated model that has shown a greater capacity to explain more of the variance in the dependent variable of "technology utilization" than previous models, adds to this thesis's credibility and makes it a valuable addition to the existing literature.

According to the finding of the survey used for this thesis, most of the respondents, regardless of gender, agreed that AI plays an important role in radiology. Specifically, 57 out of 119 (47.90%) respondents strongly agreed, and 48 out of 119 (40.34%) agreed, which counts for 88.24% of all the participants. Considering these results, as an attempt to answer the first research question: *"How do radiology professionals perceive the usefulness of AI applications in radiology settings?"* the answer is that most of the participants positively perceived the usefulness of AI applications in radiology. As the answer to the second research question of this study: "*What are the main predictors of radiology professionals' perception of AI usefulness?",* the result of this study shows that among all the considered independent variables for this study, predictors including*: "AI Future Impact", "AI working knowledge", "AI experience", "AI Feelings", "AI Challenge-Implementation",* and *"AI App-Quality Control*" have the strongest correlation with the dependent variable of "AI Perceived Usefulness" and therefore can strongly explain the perception the radiology professionals may have toward AI usefulness in the radiology practices.

The result of this study also showed that the strongest positive correlation (0.587) occurs between "AI Future Impact" and the dependent variable of "AI Perceive Usefulness". This

relationship was significant with a p-value less than 0.001 (B = 0.671, t = 7.613). This is justifiable as the more radiology professionals believe that AI will take place in many applications and image production in their practice, the more confidence they will have in the role of AI in their practice and therefore they will be more inclined to recognize the importance of implementing AI into radiology practices. This will indeed result in a higher level of perceived AI usefulness among radiology professionals. Although according to the TAM/TTF integrated model, there is a negative relationship between "Tool Functionality" and " Perceived Ease of Use" which can be interpreted in the way that technologies with a higher range of functionality are more likely perceived as more challenging to use or operate (Dishaw & Strong,1999), the results of this study show that there is a positive relationship between "AI Future Impact" and "AI Perceive Usefulness" that is mediated by "AI Perceived Ease of Use". This could be ascribed to the culture of developing countries as the technology users may believe the higher the level of technology functionality, the easier it is to utilize due to its automation.

Considering the TAM/TTF model, where "Tool Functionality" has a direct relation with "Task-Technology Fit", in this study, as part of "Tool Functionality", the "AI Future Impact" also has a direct relation with "Task-Technology Fit" or "AI Feeling" in the study's proposed theoretical framework. The positive relationship which exists between "Tool Functionality" and "Task-Technology Fit" is also supported by a number of previous studies as well (Goodhue,1995; Goodhue & Thompson, 1995).This can be interpreted in the way that the greater the level of "AI Future Impact", the more likely the radiology professionals will think that the AI functionality will help them to fulfill the requirement of the task they need to accomplish, therefor they feel better toward the use of AI applications in their practices.

As part of “Tool Functionality”, the result of this study also shows that “AI Challenge-Implementation” has a negative correlation (- 0.187) and a significant effect on “AI Perceived Usefulness” (B = - 0.375, t = - 2.589, p = 0.011) which is mediated by “AI Perceived Ease of Use”. This could be due to the fact that the greater the radiology professionals’ perception of the challenges involved with AI implementation, the less likely they regard AI as an easy tool to be used and eventually the less likely they may perceive AI as a tool that plays an essential role in their practices. On the other hand, if radiology professionals perceive an increase in the number of challenges resulting from AI implementation, they will be less likely to perceive AI as an efficient tool for accomplishing the requirements of their practice. This may influence how they evaluate the AI's suitability for their tasks, potentially leading to negative feelings toward AI applications in radiology settings.

According to the results of this study, “AI Feeling” appeared to be one of the main predictors of “AI Perceived Usefulness” among radiology professionals. The findings of the study show that “AI Feeling” has a positive correlation (0.301) and significant effect (B = 0.124, t = 2.702, p = 0.008) on the “AI Perceive Usefulness”. Like the results of the prior research studies, this relationship can be assigned to the fact that when the technology has greater capabilities to fulfill the requirements of the task, the radiology professionals will be more likely to build a positive feeling toward using that specific technology (AI). This positive evaluation of task-technology fit represents the feeling radiology professionals have toward using AI. The more positive “AI Feeling” would be the greater level of “AI Perceived Ease of Use” will be obtained which consequently will result in a more positive radiology professionals’ perception of AI Usefulness.

As a part of the study's result, it is evident that "AI App-Quality Control" is one of the main predictors of "AI Perceived Usefulness". According to the finding of the study, quality control was among the most needed AI applications reported by radiology professionals who participated in the survey. Quality control was reported as a required application to be fulfilled with the help of AI as a part of the "Clinical Task Characteristic". According to the finding of the study, "AI App-Quality Control" has a positive correlation (0.178) and significant effect (B = 0.248, t = 2.294, p = 0.024) on the "AI Perceive Usefulness". However, this relationship is mediated by "AI Feeling" and "AI Perceived Ese of Use". Although in the TAM/TTF integrated model, there is a negative relationship between "Task Characteristics" and "Task-Technology Fit (TTF)" which suggests that the TTF may decrease as the task requirements increase since the task may become too complex for the IT solution to provide the required support (Dishaw & Strong, 1999). However, this relationship is positive according to the results of the current study. The reason for this could be because the AI applications which support radiology quality control are already available and are not something beyond the potential and capabilities of radiology AI applications. Therefore, as the radiology professionals perceive that their clinical task requirements for radiology quality control can get fulfilled with the help of AI applications, their positive feeling toward AI may grow stronger, resulting in an increased level of "AI Perceived Ease of Use" and a more favourable assessment of AI usefulness.

The findings of this study along with earlier research studies including Dishaw and Strong (1999), showed that "AI Experience" is among the main predictors of "AI Perceived Usefulness". As argued by Rouidi et al. (2022), the studies show that when the users' knowledge of IT is high, they perceive less effort to use that particular technology, therefore, the "Perceive

Ease of Use" will be high which eventually will result in an increase in "AI Perceived Usefulness". However, the result of this study unlike the earlier research studies, shows that the "AI Experience" has a negative correlation (- 0.055) and significant effect (B = - 0.105, t = - 3.035, p = 0.003) on the "AI Perceived Usefulness". This could be due to a variety of factors including contextual or cultural influences. One of the potential reasons may be the fact that those radiology professionals who have utilized AI applications for a longer period of time and have gained more experience using AI, often are more aware of consequences related to the ethics, governance, accountability and responsibilities they might get involved in case of any miss-diagnosis or error related to AI applications, therefore they may have negative perceptions toward the use of AI.

The findings of the study show that "AI Working Knowledge" has a positive correlation (0.317) but an insignificant effect (B = 0.104, t = 1.868, p = 0.064) on "AI Perceived Usefulness". Unlike other considered independent variables in the model that were significantly related to the "AI Perceived Usefulness" at a p-value of 0.02 or less, the "AI Working Knowledge" variable did not show a significant relationship with the "AI Perceived Usefulness" (p =0.064). One of the potential explanations may be the fact that those radiology professionals who have used AI applications at their work and have more working knowledge of AI, might be more familiar with the challenges involved in using AI applications in their practices. As a result, they might be more resistant to adopting AI solutions and they might not perceive AI as a useful tool to be implemented in radiology settings. Another reason could be the perception some radiology professionals may have regarding the fact that AI may replace them. This perspective may lead them to be pessimistic regarding the implementation of AI in radiology practices in the

way that they simply don't want to recognize or perceive the usefulness of AI applications.

Considering the model as a whole, the results of multiple regression analysis to examine the relationship between the independent variables ("AI Future Impact", "AI Feeling", "AI Working Knowledge", "AI Experience", "AI Challenge-Implementation" and "AI App-Quality Control") and the dependent variable, radiologist professionals' perceived AI usefulness, indicate that the model is significant ($F = 17.994$, $p < 0.001$). The model also shows that the independent variables together accounted for a significant amount of variance in the radiology professionals' perceived AI usefulness. The correlation coefficient (R) was found to be 0.701 which demonstrates a positive strong linear relationship between the independent variables and radiology professionals' perceived AI usefulness. The coefficient of determination (R-squared) was 0.491, indicating that 49.1% of the variance in radiologist professionals' perceived AI usefulness can be explained by the variance in the independent variables. These outcomes indicate that the independent variables have a considerable impact on radiologist professionals' perceived AI usefulness. The study model suggested the significance of considering these independent variables in designing and implementing AI systems in radiology settings.

7. Conclusions

This study is one of the rare studies evaluating the perception radiology professionals may have toward AI usefulness by proposing a theoretical framework that can explain this perception. Considering the superior explanation power that TAM/TTF integrated model has compared to earlier models, adopting such a reliable model made this thesis credible enough to add to the available literature. This study can be considered reliable not only to understand the

perception radiology professionals may have toward AI usefulness but also to get valuable knowledge about "How to improve the actual use and the adoption of AI applications in radiology settings". According to the result of this study, factors such as AI functionality and future impacts; challenges associated with using AI such as AI implementation challenges; radiology professionals' AI experience; AI capabilities to provide clinical support such as quality control; and the radiology professionals' overall feeling toward AI are among the most significant factors influencing the way radiology professionals perceiving AI usefulness.

To improve the AI perceived usefulness among radiology professionals, this study suggests that healthcare management and administration departments consider providing reliable education and training courses to improve the knowledge and understanding that radiology professionals may have about AI applications in radiology practices. It is also essential to address AI challenges specifically those challenges that are associated with implementing AI systems in the radiology settings. This could result in improving the positive perception radiology professionals may have toward the use of AI by providing more positive AI user experiences.

7.1. Study Limitations and Future Research Recommendations

Despite the fact that this study is one of the rare research studies that have contributed to identifying factors impacting the radiology professionals' perception of AI applications in radiology practices, like any other study, this study has a few limitations. Firstly, this study used the generic term "AI" without determining any particular type of AI application in the medical imaging department. It is essential to understand that the evaluated "AI perceived ease of use"

and “AI perceived usefulness” reported by participants may vary depending on the type of AI application being evaluated. To acquire a better understanding of the factors influencing the perceived usefulness of AI in medical imaging and move toward the successful implementation of specific AI clinical tools in radiology practices, future research should focus on evaluating the radiology professionals’ perception of a specific AI clinical tool rather than using the general term of “AI”.

Secondly, due to ethical reasons, the specialty of the participants was not disclosed in this study. However, depending on the nature of their work and the tasks they need to accomplish using AI applications, different radiology professionals may perceive the usefulness of AI applications in different ways. As a result, it is highly recommended that future research studies consider conducting separate studies for each specialty involved in the medical imaging department. Additionally, it is extremely important to acknowledge that successful AI implementation in radiology departments is not solely dependent on the factors impacting the perceptions of radiologists or radiographers. In fact, many other factors related to organizational readiness and economic aspects of AI implementation may also play a significant role. Therefore, to attain a more precise and trustworthy understanding of factors influencing the successful AI implementation in radiology departments, in addition to evaluating radiology professionals’ perceptions, future studies should also take into account investigating the viewpoint the hospital management and administrative departments may have toward implementing AI applications in radiology departments.

With reference to the additional insights that have been provided in section 3.10 of this thesis, although, it has been noticed that the majority of participants (88.24%) agreed that AI

plays an important role in radiology practices, however, when participants were asked how well do they understand AI, 46 (38.66%) participants confirmed either they have no idea about AI or having a limited AI understanding. On the other hand, the assessment of participants' level of AI knowledge reveals that 85 (71.43%) participants have only a basic understanding of AI. These results confirm that a considerable number of participants had a low understanding of AI, and their perception of AI usefulness may not be based on the true understanding of AI. Therefore, participants' level of AI perceived usefulness may not be as accurate as it has been reported. As a result, it is highly recommended that future research studies consider including participants who have a comprehensive perception and true understanding of AI applications in radiology.

Last but not least, the survey used by this study was conducted among radiology professionals located in the United Arab Emirates. Given the cultural difference and dissimilarities of different healthcare settings in different geographical regions, the result of this study may not be generalizable. Therefore, it is highly recommended that future studies consider the cultural and psychological aspects of radiology professionals while evaluating AI's perceived usefulness in the radiology department, particularly if they aim to adapt the results of the research to other regions and cultures.

With reference to the knowledge the researcher of this study gained by conducting a systematic literature review considering the same topic prior to this thesis, it is evident that a similar topic has been covered by a limited number of studies, with most studies being quantitative research studies. To the best of the researcher's knowledge, no qualitative research has been performed evaluating the perceived usefulness of AI in the radiology department adopting the TAM/TTF integrated model. As a result, the researcher intends to address this

research gap by conducting a qualitative research study on the same topic as part of her future research journey.

Appendices

Appendix A: The Study Survey

The Impact of AI in medical diagnostic imaging: study of radiology professions (radiologists, radiographers) perceptions, knowledge, and willingness to accept AI implementation in practice

Part 1: Demographic data:

1. **Gender: _____**
2. **Age: _____**
3. **Highest qualification attained.**
    a. Diploma,
    b. B.Sc.,
    c. M.Sc.,
    d. Ph.D.,
    e. Fellowship,
    f. Other _____
4. **How long have you practice experience in medical imaging (year)? _____**

Part 2: Perceptions

Item	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
1. AI will play an important role in the practice of radiology professions.					
2. AI will take place in many applications and image production such as quality control, dose selection and image interpretation.					
3. AI will threaten/disrupt the radiology professions' practice.					
4. AI will threaten/disrupt some radiology professions' career.					
5. AI has no limitations in my work					
6. I am ready to learn and apply AI in my practice					

7. **How do you feel about AI?**
    a. Excited
    b. Aware of the challenges
    c. Neutral
    d. Overwhelmed, I don't feel I can keep up
    e. Worried about the impact
    f. I don't know enough

Part 3: Knowledge and skills

8. **How well do you understand what is meant by AI?**
    a. I've no idea
    b. Only what I've read in news, posters or media
    c. I'm familiar with it but wouldn't confidently apply that knowledge at work
    d. I'm comfortable with what it means, but I'm not technical
    e. Very comfortable. I work in AI

Item	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
9. All radiology professions curriculum include at least some basic knowledge of AI.					
10. AI should be taught in the undergraduate programme					
11. AI should be taught in the postgraduate programme					
12. I have a basic understanding of AI (relevant to my field).					
13. I have a working knowledge of AI (relevant to my field).					
14. I have been trained and educated about the AI (relevant to my field).					

	Self-taught	*Attending courses*	*Postgraduate training*	*Work-related activities*	*No knowledge*
15. My knowledge of AI is					

16. My skill in AI is developed through					

Part 4: Willingness, status and Challenges

17. At my organization, there is someone responsible for AI

a. Yes
b. No
c. I'm not sure

18. For my work AI is

a. A big part of what we do
b. A small part
c. We're beginner
d. It is future plan
e. We are not looking at or planning for
f. I have no idea

19. Does your work organization have a strategy for AI?

a. Yes
b. No
c. We're developing one
d. I have no idea

20. What are the biggest challenges for AI implementation in your work?

a. Knowledge
b. The skills development
c. It is hard to find good education and training courses in AI
d. It is hard to educate and trained the current staff in AI technology
e. It is hard to implement AI in the work and practice
f. Graduates aren't learning the AI knowledge and skills at university

21. Which AI relating application do you most need in your work?

a. Dose management
b. Quality control
c. Image evaluation
d. Image interpretation
e. Image post processing
f. Communication
g. Teaching and mentoring
h. Others; please state _____

Appendix B: Research Ethics Board (REB) Approval

Toronto Metropolitan University

Research Ethics Board

To: Fatemeh Yahyaeinejad
Ted Rogers School of Management

Re: REB 2023-086: Artificial intelligence (AI) in radiology practice: the quantitative analysis of the perceptions of radiographers towards AI

Date: April 13, 2023

Dear Fatemeh Yahyaeinejad,

The review of your protocol REB File REB 2023-086 is now complete. The project has been approved for a one year period. Please note that before proceeding with your project, compliance with other required University approvals/certifications, institutional requirements, or governmental authorizations may be required.

This approval may be extended after one year upon request. Please be advised that if the project is not renewed, approval will expire and no more research involving humans may take place. If this is a funded project, access to research funds may also be affected.

Please note that REB approval policies require that you adhere strictly to the protocol as last reviewed by the REB and that any modifications must be approved by the Board before they can be implemented. Adverse or unexpected events must be reported to the REB as soon as possible with an indication from the Principal Investigator as to how, in the view of the Principal Investigator, these events affect the continuation of the protocol.

Finally, if research subjects are in the care of a health facility, at a school, or other institution or community organization, it is the responsibility of the Principal Investigator to ensure that the ethical guidelines and approvals of those facilities or institutions are obtained and filed with the REB prior to the initiation of any research.

Please quote your REB file number (REB 2023-086) on future correspondence.

Congratulations and best of luck in conducting your research.



Dr. Asher Alkoby, LL.B., LL.M., S.J.D.
Chair, Toronto Metropolitan University Research Ethics Board
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The Following protocol attachments have been reviewed and approved.

- Ethic Approval -Sharjah University.pdf (submitted on: 17 Mar 2023)
- REB- tcps2_core_certificate.pdf (submitted on: 17 Mar 2023)
- References.pdf (submitted on: 17 Mar 2023)
- Survey -REB.docx (submitted on: 23 Mar 2023)
- Email Communication.pdf (submitted on: 23 Mar 2023)

If any changes are made to the attached document throughout the course of the research, an amendment MUST be submitted to, and subsequently approved by the REB.

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